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Model of division of labor in artificial society with continuous demand and in industrial cluster with positive social influence

Saurabh Singh

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By

Saurabh Singh

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By

Saurabh Singh

APPROVED BY:

____

Y. Aneja, External Reader
Odette School of Business

____

D. Wu, Internal Reader
School of Computer Science

____

Z. Kobti, Advisor
School of Computer Science

September 13, 2013

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ABSTRACT

Two models of division of labor or specialization, in two different systems are proposed in the thesis. The domain of the first one is the artificial society where as the second is concerned with the industrial cluster. There are several models for the emergence of increase in division of labor in agent societies. Two such models are the Genetic Threshold Model (GTM) and the Social Inhibition Model (SIM). Combining these two concepts, we propose a hybrid model for the emergence of division of labor as a function of demand varying continuously over a suitably chosen smooth curve. In the second model, we introduce a new concept of positive social response in modeling adaptive behavior of industry cluster and a new formulation for work load of an organization for a single task at a time in the cluster.

DEDICATION

To my loving parents whose immense patience and faith in me have got me this far in my life.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

A multi agent system (MAS) is a computerized system composed of several interacting intelligent agents within an environment. In agent based modeling, a system is modeled as a collection of autonomous decision making entities called agents. An agent based model (ABM) is a class of computational models for simulating the actions and interactions of autonomous agents for assessing their efforts on the system as a whole. Agent based modeling is a powerful simulation technique that has seen a number of applications in the last decade and it can be used to solve various complex problems that are related to medicine, aerospace and real world business problems. Agents are heterogeneous and their characterization depends on the context of research being done. According to Russell & Norvig (1995), an agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors. An agent can represent a human, where the sensors are the senses and the effectors are the physical body parts. An autonomous agent is capable of learning from experience and its behavior is determined by this experience. An agent can interact in a dynamic environment where they can influence other agents to change their actions or decision, and also share knowledge.

According to Spencer, Couzin, & Franks (1998), specialization or division of labor (DOL) is allocating a disproportionate amount of resource to one task compared to other available tasks. Specialization is one of the primary attributes of sociality. Archaeologists study specialization to understand changes in societies as a result of the emergence of specialization. From a biological point of view, specialization helps to find out the life cycle pattern of several species such as ants, birds, fish and wasps. Their lifecycle pattern is based on task selection. In the business field, specialization plays a key role on the economy and hence the dominance of the organizations by increasing the productivity Task selection, task performance, task overload, as well as the demand and supply of tasks that are the other major factors which affect society's economy.

According to Wei & Feifan (2009), an industry cluster is a geographic concentration of interconnected businesses including suppliers and manufactures in a particular field. Porter (1998) is the person who coined the idea of an industry cluster. He showed that clusters have a capability to increase the productivity of the companies in the clusters. According to his findings in "The competitive advantage of nations", he concluded that companies gain advantage against the world's best competitors because of pressure and challenge. Some important examples of industry clusters are Silicon Valley of the United States and Guangdong, Jiangsu, Zhejiang in China (Yang & Niu, 2013). Silicon Valley is famous for its software hub. Companies start growing because of a competitive and cooperative advantage of the other organizations in the cluster. There is no proper guideline and definition of an industry cluster because it depends upon how cluster grows in a specific area. The overall picture behind an industry cluster is to understand our regional economy.

1.1 **Current research motivation:**

There are several different ways to cause the emergence of specialization within a complex system but each of these works with the limitations of their own assumptions and contexts thus making it difficult to compare results across these different approaches. In some of the earlier models, agents were restricted to do one or at most two tasks but not more than that. Cockburn & Kobti, (2011) and 2012 created a weight allocated social pressure system for the emergence of agent specialization (WASPS) where more skilled agents inhibit the desire of less skilled agents to perform a task. This model analyzed the emergence of agent specialization in multi agent systems. In this model an agent can perform multiple tasks by allowing agents to divide a given resource among the available tasks. Though their approach was inspired by social insects, this approach is entirely applicable to agents in other domains. Combining the Genetic Threshold Model (GTM) (Beshers & Fewell, 2001), and the Social Inhibition Model (SIM) (Beshers & Fewell, 2001), in 2012 they proposed a hybrid model (Cockburn & Kobti, 2012) aiming to increase the effect of agent skill on a task choice when agents possess different aptitudes for tasks. According to the genetic thresholds model each task has certain level of stimulus at which an individual will choose to specialize in that task. The genetic thresholds model is related to evolutionary behavior, as agents that respond to stimuli quicker are more likely to survive. Social inhibition model implies that an agent chooses their specialization, they notify other agents that have done so, hence reducing the desire of other agents to choose that task. Their model increased the level of quality of work (QOW), but with the side effect of reduced levels of specialization. In their model, agents choose randomly among tasks with surpassed threshold or be inactive if no such task exists. They assumed that each time a task i is performed by an individual; the stimulus intensity S_i is decreased by an amount α=3 For each time step, the level of stimulus S_i associated with task i is increased by $\beta_i = \alpha \frac{N}{T}$, where N is the group size (number of individuals) and T is the task number. The reduced demand consequent with increased group size should positively affect DOL as shown by (Jeanson, Fewell, Gorelick, &

Bertram, 2007). So they had incorporated demand δ in the expression for β_i . But they fixed the demand for all tasks thus the rate of stimulus regeneration is identical for all tasks and does not vary with time.

The decreased level of specialization in WASPS model (Cockburn & Kobti, 2012) and the identical rate of stimulus regeneration in (Jeanson, Fewell, Gorelick, & Bertram, 2007) motivated us to present our work in Chapter 3, as we believe this is not very realistic so we let the rate of stimulus regeneration vary over time. This is achieved by considering the demand δ varying continuously over a smooth curve.

The positive social influence, the workload and consequent to the workload, the adaptation of cooperative behavior missing from these and several other models were the motivation for the industrial cluster model presented in Chapter 4.

1.2 **Thesis Contribution**

We modified the previously existing WASPS model (Cockburn & Kobti, 2011) and (Cockburn & Kobti, 2012) by replacing the formula for the genetic pull given in there by a new formula and introducing the concept of randomly chosen and continuously varying demand over a suitably chosen smooth curve to study the emergence of specialization and QOW in an artificial agent society. We tested our model with discrete, random and continuous demand and achieved better level of DOL and QOW compared to this model and the one proposed by (Jeanson, Fewell, Gorelick, & Bertram, 2007).

Though the proposed modified model is a good computational model of specialization, it is practically not feasible to study the specialization in an industry cluster as there are several key features which are essential in an industry cluster and are missing in the model. So we propose a model which can be applied to various fields, especially to an industry cluster to analyze the division of labor there.

Adaptation helps the individual organization to adjust its behavior so as to achieve healthy growth of both the individuals and the whole industry cluster as well. We propose a new industry cluster model adaptation based on two new concepts: (i) The Score function f_t, a parameter depending on the positive social influence and (ii) a new formulation for the work load $\gamma_{x,j}(t)$ (of an organization x for the task j at time t) depending on the stimulus intensity $S_{x,j}(t)$ via the Bessel function J_3. The model is tested through numerical simulation for the emergence of specialization in the cluster.

In our industry cluster model we demonstrated that individual organizations which are connected in small world network are competing for a common goal which is task in our case. In order for an individual organization to select a task, we used social influence concepts and constructed our own formula for task selection. We also incorporated the formula for task workload and cooperative behavior and demonstrated that in critical situation when any individual organization is suffering from task work load then cooperative behavior emerges from other organizations causing the increase in specialization.

1.3 **Thesis Outline**

The main aim of this research is twofold: the first is to improve the previously existing WASPS (Cockburn & Kobti, 2011) and (Cockburn & Kobti, 2012) model to achieve better levels of specialization and quality of work and the second is to propose a new model of adaptation of positive social response in an industry cluster. In order to discuss this, we divide the thesis into following chapters.

In chapter 2, a short literature review of some recent work on the genetic thresholds model, social inhibition model and industry cluster model is given.

"A Hybrid Model for Emergence of Skilled Agent Specialization with Continuous Demand" (Singh, Shah, & Kobti, 2013) is proposed in Chapter 3. A new mathematical formulation is given for genetic pull to improve DOL and QOW compared to the existing WASPS model. The novelty of this chapter is the introduction of demand varying continuously over a suitably chosen smooth curve.

A new idea of positive social response in task selection in an industry cluster is introduced to build a new model of adaptation in the cluster in Chapter 4. The emergence of cooperative behavior due to positive social response and its effect on the increase in specialization is discussed in there as well.

CHAPTER 2

Literature Review

A literature survey pertinent to the work of the thesis is summarized in this Chapter. So, a short description of specialization models in artificial society and in industry cluster is given.

In artificial society, agents are able to reason about the environment in order to maximize the performance to achieve their individual goals. There are many ways by which agents can improve their task performance and increase the productivity. Some of the approaches are: (i) Agents can learn from their past experience and improve, (ii) Agents can interact within the same group or across the other groups to discuss about the demand and supply of a particular task, and (iii) Agents can choose to pick tasks on the basis of skill inheritance from the family.

Industry clusters is a group of some interactive relevant enterprises, specialization suppliers, service providers, financial institutions, relevant industrial manufacturers and other related organizations with all these members of the group settling in a special region. They cooperate as well as compete with each other.

Specialization or division of labor is the spending of a disproportionate amount of a resource on one task compared to other available tasks. In other words, division of labor is fundamentally a stable pattern of variation among the workers within a colony in the tasks they perform. Division of labor or specialization is one of the most basic and widely used terms in social insects colony. Social insect colonies are groups of individuals that live together and reproduce as a unit. Two general patterns of division of labor are recognized in social insects: temporal polytheism or age correlated patterns of task performance, and morphological polytheism, in which a worker's size and or shape are related to its performance of tasks. Temporal polytheism is common in the social insects colony where the younger workers perform the task within the nest and the older workers with more experience perform the outside tasks such as foraging and defense. Morphological polytheism is found in termites and in those ant species with pronounced sub castes within the worker cast. Patterns of morphological polytheism are variable; one generalization that appears to hold is that the more extreme sub castes, in either size or morphology, have more specialized behavior and narrow repertoires. The most common specializations are for defense and foraging. Food processing and its storage are the other roles of morphologically specialized workers (Beshers & Fewell, 2001), (Arnold & Munns, 1994) and (Jaisson, Lecoutey, Kaminski, Châline, & Pierre, 2007).

The earlier research on division of labor was focused to find correlations between behavior and worker age or morphology and to define behavioral castes on the basis of these correlations (McCarthy & Enquist, 2003).

Besides the above points, an important concept of division of labor is the task selection. This is one of the important and promising features of the division of labor. There are several factors affecting the choice of a worker for a particular task. All these factors are divided into two categories as internal and external factors. Internal factors are genetic, neural, hormonal and the effect of experience of worker whereas the external factors include the task specific stimuli and interactions between the workers regarding the task selection. From now onwards, we will mean a worker as an agent and a colony of workers as an artificial agent's society and interchange these words frequently without any ambiguity.

It is quite possible that internal and external factors interact and cause changes in the environment. Like interactions between the workers/agents may also affect individual's motivational state. On interactions, an agent may positively influence another agent or inhibit his desire to perform the task. An agent's successful performance of a task may also increases his intrinsic probability of performing that task again. The performance of a task by an agent affects the stimuli perceived by the rest of the colony (Beshers & Fewell, 2001).

There are several different ways to cause the emergence of specialization within a complex system. The agents may choose their specialization or it may be assigned as is the case in caste system. Several factors including genetic, social and economic considerations affect the choice of specialization (Singh, Shah, & Kobti, 2013), (Bourke, 1999) and (Arnold & Munns, 1994).

Several genetic models have been proposed for the study of specialization. The most widely used is the response thresholds model (Beshers & Fewell, 2001). The thresholds model presents a certain level of stimulus for each task at which an individual will choose to specialize in that task. In the threshold model, agents by default perform no tasks. It means if there is no stimulus for any of the possible tasks, then the individual will do nothing. In some approaches, performing a task causes the thresholds level for that task to decrease, while not performing the task will lead to the thresholds level increasing (Singh, Shah, & Kobti, 2013) and (Anderson & McShea, 2001).

Genetic thresholds model (Beshers & Fewell, 2001) demonstrates that agents have inner thresholds for responding to task specific stimuli and that variation in task thresholds among agents in a colony generates division of labor. Thresholds models relate the internal threshold, the perceived stimulus, and the decision to perform a task. The thresholds model presents a certain level of stimulus for each task at which an individual will choose to specialize in that task. In the threshold model, agents by default perform no tasks. It means if there is no stimulus for any of the possible tasks, then individual will do nothing. Agents will also perform no tasks if none of the stimuli for all available tasks fail to cross its response threshold. The threshold varies between agents.

Naug and Gadagkar, (1999) extended the Huang and Robinson model to explain the social inhibition. In (Naug & Gadagkar, 1999), each agent has two pods, one pod contains an activator that increases its own preference for a task, and another pod contains inhibitor which inhibits the preference of other agents it interact with for the same task. They assumed that all agents have the same skill level and same preference for the entire task which is not very realistic.

Gordon, Goodwin and Trainor, (1992) presented the social interaction model where each agent had an active and inactive state for the four tasks in the model. Each agent communicates with other agents where they share information regarding how many other agents are performing the same task. The idea presented here is good because in a system it is very important to know what others are doing but the model is fraught with limitations. The main problem with this model is that it did not give any preference to task. Hence, all agents will handle each task with the same preference and with the same skill. Total number of tasks being 4 in this model is also a serious limitation. Further, demand, one of the crucial parameters in the emergence of division of labor, is missing in the model (Gordon, Goodwin, & Trainor, 1992).

Spencer, Couzin and Franks, (1998) proposed a model of specialization in which agents encounter one or more task in their environment. At each time step of the simulation, agent may perform one task. If it performs a particular task, its propensity to perform that task increases. If it does not perform a task, its propensity for performing the task decreases. They state that tasks are abstracted as discrete items, one task item being defined as the amount of task that one agent can complete in one unit of time. For the simplicity they did not specify time scales and not modeled the effects of changing task efficiency. All the parameters of the model scale with the time step. The reasons for this is that time scales for different organisms are likely to differ over several orders of magnitude, and the time period represented by one time step must reflect the behavior under consideration (Spencer, Couzin, & Franks, 1998).

Jeanson, Fewell, Gorelick, & Bertram (2007) demonstrated in their model that any individual can be in two states: inactive or engaged in one task. At each time step, an inactive individual *i* randomly encounters all available tasks. An individual starts performing the first randomly encountered task for which the intensity of the stimulus is higher than its corresponding intrinsic thresholds. The level of stimulus for any given task perceived individually by workers and compared to their individual response thresholds is determined by the total level of the stimulus associated with that task divided by group size. The effect of demand on emergence of division of labor as a function of group size was analyzed where demand represents the total colony effort required to complete all tasks relative to the available total effort from workers. However they fixed the demand for all tasks thus the rate of stimulus regeneration is identical for all tasks and does not vary with time. This is not an ideal case because demand of task may vary with time and it may not be constant through the entire simulation.

In 2003 another specialization model was given by (Lavezzi, 2003). Lavezzi concluded that specialization depends upon many factors like competition between agents, agent's connectivity, and his thresholds. Two important points were discussed: 1) how competition between agents will affect the choice of agent specialization, and 2) how thresholds distribute between agents. Agents of course have to know about the level of competitions, or be directly aware of the changing stimulus level and are also required to have excess knowledge of their economic environment.

The existing social models have several other shortcomings. In most of the existing models agents are only able to perform one task per unit of time. Cockburn and Kobti in 2011 presented a WASPS model which deals with situations where agents can divide their time among several tasks. In the WASPS model (Cockburn & Kobti, 2011) and (Cockburn & Kobti, 2012), agents are allowed to perform more than one task. Each agent has skill level specific to a particular task. Their model uses the key features of genetic thresholds model and social inhibition model to select the task. By combining these two features agent will select tasks according to their thresholds and skill level related to that task. We took the features from WASPS model and proposed a hybrid model improving the division of labor significantly in an artificial society. A detailed description of their model is given in chapter 3 of the thesis.

Specialization increases the productivity and economy of a system specially an industrial cluster. So it is very important to study the emergence of specialization in industry clusters. Industry clusters is a group of some interactive relevant enterprises, specialization suppliers, service providers, financial institutions, relevant industrial manufacturers and other related organizations with all these members of the group settling in a special region.

Wei & Feifan (2009) proposed an adaptive model for industry cluster in which they used the features of genetic thresholds model for task selection. In their formulation stimulus intensity is the driving force for individual enterprise to select a task j. The more the stimulus, the more attractive the task is to the individual enterprise in the cluster. The response threshold is updated in self-reinforcing way. If it selects the task j, enterprise i become more or less sensitive to stimulus by decreasing the thresholds. In addition, the enterprise workload is used as a feedback for response thresholds, allowing thresholds to increase when the workload is high. The novelty of their model is that they introduced the idea of task workload. The detail of task workload of their model is given in Chapter 4. The model formulates the adaptive behavior of the industry cluster mathematically without any numerical simulation, a vital feature to test the model.

CHAPTER 3

A Hybrid Model for Emergence of Skilled Agent Specialization with Continuous Demand

3.1 Preface

In this chapter we study the effect of demand on specialization of skilled agents by modifying the earlier hybrid model which is based on the well-known Genetic Threshold Model (GTM) and Social Inhibition Model (SIM). We improve the agent specialization or division of labor (DOL) and also the quality of work (QOW) by introducing a new concept of varying the demand on a smooth curve and compare our results with the previous models.

3.2 Introduction

In an artificial society, agents are able to reason about the environment to maximize the performance to achieve their individual goals. There are many ways by which agents can improve their task performance and increase the productivity. Some of the approaches are: (i) Agents can learn from their past experience and improve, (ii) agents can interact within the same group or across the other groups to discuss about the demand and supply of a particular task, and (iii) agents can choose to pick tasks on the basis of skill inheritance from the family.

According to (Spencer, Couzin, & Franks, 1998) specialization is allocating a disproportionate amount of a resource to one task compared to other available tasks. In population of heterogeneous individuals, it is often the case that these individuals possess different aptitudes for available tasks. Individuals increase their productivity by enhancing their specialization in communities of mutual interest, whereby other individuals are also trying to maximize their productivity in relation to competitors.

Division of labor or specialization is one of the primary attributes of sociality. Caste and specialization have been the focus of the study of the organization of insect societies for more than fifty years (Maynard Smith & Szathmary., 1995). Indeed, the description and analysis of task allocation between colony members are fundamental to understand the organization of a complex biological system whose functioning depends upon the behavioral integration of a potentially large number of individuals or agents. The advantage of specialization by individuals within the groups is also considered to be of overwhelming importance in many of the major transitions in the evolution of life.

The evolutionary transition from solitary organisms to highly integrated societies composed of individual organisms (e.g. ant colonies, termite colonies and certain bees and wasps) is also associated with efficiencies that accrue from a division of labor and task specialization. Social insect colonies have been compared to factories within fortresses and there are many different tasks that agents (workers) must perform, from building the nest and guarding the colony to tending the queen, rearing many different stages of brood, and feeding and grooming one another (Oster & Wilson, 1978). Division of labor, where different units within a system perform different tasks, is a recurrent property of association of multiple entities and a hallmark of social living. This fundamental property has been described across a diversity of social taxa, from simple to complex groups. However, empirical evidence suggests that division of labor in social groups increases with increasing group size (Bourke, 1999) and (Anderson & McShea, 2001). Larger groups size is phylogenetically correlated with more complex and derived sociality, as seen recurrently within the social insects (Oster & Wilson, 1978), suggesting that the pattern may reflect selection acting to increase individual specialization. There is also a trend towards increased division of labor during social ontogeny, as social groups grow from few individuals to many, as shown in (Karsai & Wenzel, 1998) and (Thomas & Elgar, 2003). A model providing insight into possible mechanisms contributing to division of labor was given in (Jeanson, Fewell, Gorelick, & Bertram, 2007) and it was shown that an increase in division of labor could parallel an increase in group size directly via the distribution of thresholds within groups and indirectly via by-products of increased group size (i.e. task number and demand).

There are several different ways to cause the emergence of specialization within a complex system. The agents may choose their specialization or they may be assigned as is the case in caste system. Several factors including genetic, social and economic considerations affect the choice of specialization (Beshers & Fewell, 2001), but no approach can fully explain specialization in a complex system (Traniello & Rosengaus, 1997). These different approaches work with the limitation of their own assumptions and contexts thus making it difficult to compare results across these different approaches (Kobti & Cockburn, 2011).

Several genetic models have been proposed for the study of specialization. The most widely used are the response thresholds model. The thresholds model presents a certain level of stimulus for each task at which an individual will choose to specialize in that task (Theraulaz, Bonabeau, & Deneubourg., 1998). In the threshold model, agents by default perform no tasks. It means if there is no stimulus for any of the possible tasks, then individual will do nothing (Beshers & Fewell, 2001). Agents will also perform no tasks if none of the stimuli for all available tasks fail to cross its response threshold. The threshold varies between agents. In some approaches, performing a task causes the thresholds level for that task to decrease, while not performing the task will lead to the thresholds level increasing (Theraulaz, Bonabeau, & Deneubourg., 1998).

Social inhibition models also play an important role in the emergence of agent's specialization. According to this approach agents choose their specialization, they notify other agents that they have done so, reducing the desire of others to choose this specialization.

Division of labor (DOL) and quality of work (QOW) (Cockburn & Kobti, 2012) are the two main components which are discussed as a function of discretely, randomly and continuously varying demands in this paper. The DOL statistic measures the degree to which different individuals within the group specialize on different tasks and the degree to which each individual is specialist (Jeanson, Fewell, Gorelick, & Bertram, 2007). Quality of work (QOW) measure the average amount of skill used in performing a task. The higher values of DOL and QOW are indicative of increase in specialization among the agents and that the task was performed by a more skilled agent.

(Cockburn & Kobti, 2011) and (Cockburn & Kobti, 2012) created a weight allocated social inhibition approach whereby more skilled agents inhibit the desire of less skilled agents to perform a task. This approach drives agents toward tasks where they have comparative advantages. This leads to an increase in specialization within the population. Though their approach was inspired by social insects, this approach is entirely applicable to agents in other domains. Combining the Genetic Threshold Model (GTM), and the

Social Inhibition Model (SIM), they proposed a model aiming to increase the effect of agent skill on task choice when agents possess different aptitudes for tasks. Their model increased the level of quality of work (QOW), but with the side effect of reduced levels of specialization. In their model, agents choose randomly among tasks with surpassed threshold or be inactive if no such task exists. They supposed that each time a task i is performed by an individual, the stimulus intensity S_i is decreased by an amount $\alpha = 3$. For each time step, the level of stimulus S_i associated with task i is increased by $\beta_i = \alpha \frac{N}{T}$, where N is the group size (number of individuals) and T is the task number. The reduced demand consequent with increased group size should positively affect DOL as shown by (Jeanson, Fewell, Gorelick, & Bertram, 2007). So they had incorporated demand δ in the expression for β_i as given by equation (4). But they fixed the demand for all tasks thus the rate of stimulus regeneration is identical for all tasks and does not vary with time.

The decreased level of specialization in (Cockburn & Kobti, 2012) and the identical rate of stimulus regeneration in (Jeanson, Fewell, Gorelick, & Bertram, 2007) motivated us for the present work. In this paper, we modify the model (Cockburn & Kobti, 2012) and assume the same characteristics of agents; varying skill levels for each task and the ability to divide resources among tasks. Further, we incorporate the effect of demand δ on division of labor (DOL) and quality of work (QOW); a feature missing in (Cockburn & Kobti, 2012) but taken into consideration by (Jeanson, Fewell, Gorelick, & Bertram, 2007) while analyzing the emergence of increased DOL as a function of group size by taking $\delta = 0.7$, 0.9, 1.0 and 1.1. Demand represents the total colony effort required to complete all tasks relative to the available total effort from workers. We analyze the effect of demand on DOL as well as QOW by (i) taking discrete values of δ same as in (Jeanson, Fewell, Gorelick, & Bertram, 2007), (ii) choose it randomly in (0.1, 1.1) and (iii) let δ varies continuously through a smooth curve whose profile is given in Figure 4. In the next section, we give a brief description of the model (Cockburn & Kobti, 2012) for continuity and readability of the paper.

3.3 Hybrid Model

As this model is a modification of the one proposed in (Cockburn & Kobti, 2012), the agents will have all the properties of their model like agent attributes, its inhibition, its interaction and its attribute updates. Let T denote a set of tasks i.e. each element $i \in T$, is a task to be performed by an agent. Each agent has a level of skill $Sk_a(i)$ associated with each task i. The skill level may be dynamic or static and is quantifiable and monotonic, i.e. $Sk_a(i) > Sk_b(i)$ means that agent a, is more skilled than agent b for task i. All agents assume they can perform the task perfectly. The strength of inhibition of an agent towards other agents depends upon the skill level of the agent. Agents are thus able to determine their true relative skill level through interactions with other agents. The strength of inhibition, which we refer to as the influence rate, depends on each agent. Agents have to divide their time among tasks. They therefore need to track their allocations, which they do internally. Time is simply one idea of a resource. This model does not require the resource to be time, but it can be money, food, or any other divisible resource. The simulation is composed of a set of interacting agents within a social network that can all perform the same tasks at varying skill levels.

For each agent Ag, we have a $ALLOC$ set (Cockburn & Kobti, 2012), where $e_i \in ALLOC \Rightarrow$ there is a task i in T_{Ag} with weight e_i allocated to the task i, where T_{Ag}

is the set of tasks available to the agent Ag . Similarly R_{Ag} , is the resource available to Ag to do the tasks in T_{Ag} .

Task weights in $ALLOC$ are relative, hence for a given task i , the amount of R_{Ag} to be allocated to the task i is:

$$\frac{e_i}{S(ALLOC)} \times S(R_{AG}) \quad \textbf{(1)}$$

where $S(ALLOC)$ is the sum of all elements in $ALLOC$ and $S(R_{Ag})$ refers to the total amount of resource available. A task having a weight of 0 will result in the task being allocated none of R_{Ag} . We will assume, without loss of generality, the resource R refers to the time for the rest of the paper. They also normalize the weights in $ALLOC$ such that $S(ALLOC)$ is always equal to 1.

Agents influence other agents when they interact. In some social network like kin network, it can be assumed that they interact with all their neighbors in each time step. The amount of influence is dependent on skill level. It means higher the skill level, the higher the level of influence. When an agent interacts with another, it positively reinforces its own behavior, while also inhibiting the other agent. The amount of self-reinforcement is the same amount that it inhibits the other agents. After all agents have interacted, the agent subtracts the level of inhibition it has received from the level of activation it has provided itself.

Each agent has the following attributes for all tasks $i \in T$: (i) A skill set $SKILL = \{s_i\}$ and (ii) A set $PODS = \{p_i\}$.

$s_i \in SKILL$ Represent the skill of the agent to perform the task i. The skill level for a task may be dynamic and updated regularly. For $p_i \in PODS$, p_i is a 3 tuple (A, SA, I), where A represents the activator store for the agent, SA is the level of self-activation, and I is the inhibition store for the agent. The agent will increase or decrease the weight of the associated task depending upon whether A + SA is positive or negative respectively. The idea behind self-activation is the inclination of an agent to perform more of the task at which they are best. This value should be large enough that it will allow an isolated agent to specialize over a long period of time, but it should also be small enough that it doesn't overwhelm the social pressure created by stronger competitors.

When two agents Ag_1 and Ag_2 interact, for a task $i \in T$, we obtain the values of their PODS for that task i. The interaction will decrease the value of A in their respective PODS by the other agent's I, whereas each agent will increase it's A value by its I. Agents will update their allocation based on each task pod. Given an allocation e_i and pod (a, s, x) for a task i, e_i will be updated as: $e_i = e_i + a + s$ i.e. the amount of self-activator s and activator a is added to the current weight.

After all task weights are updated for an agent, the values are again normalized, resulting in the sum of all weights being 1.

In the classical genetic thresholds model, all agents who have been activated (based on thresholds) are qualified to perform a task. It is quite possible that less qualified agents will be selected to perform the task, resulting in less-efficient task performance. This situation can be solved by agent's thresholds value.

Agents have thresholds at which they are willing to select a task. Different model have different methods to change agent thresholds. (Cockburn & Kobti, 2012), used genetic pull towards performing the task at which the agent is most skilled for changing agent's thresholds

They used the following formula for the genetic pull:

$$1 - \sin(SK_a(i)) \times 90 \times MT] \qquad (2)$$

where MT refers to the maximum threshold all agents can possess for a task. This creates a genetic stable point for agents, based on skill levels.

The reason for lower levels of division of labor in (Cockburn & Kobti, 2012) model is rather lower values of the genetic pull governed by equation (2). So, in our model, we have selected Bessel function because they behave like damped sin and cosine curves and stabilize over a longer period of time as evident from Figure 1. Blue curve represents the sin while red represents Bessel function. This is because in the beginning of the simulation, agents have high potential to perform the task but as time passes energy levels will be lowered.

We constructed the following formula for genetic pull:

$$MT \times [1 - a_n J_n\left(b_n SK_a(i)\right)] \qquad (3)$$

where $Sk_a(i)$ refers to the skill level the agent a has for task i, MT refers to the maximum threshold all agents can possess for a task, J_n is the nth order Bessel function of the first kind and a_n, b_n are the scaling factors. Thus, genetic pull creates a stable point whereby an agent lowers its threshold whenever its skill for that task is lower. It is also obvious that for agents skill level will change over time, due to this agent's genetic threshold will also change.

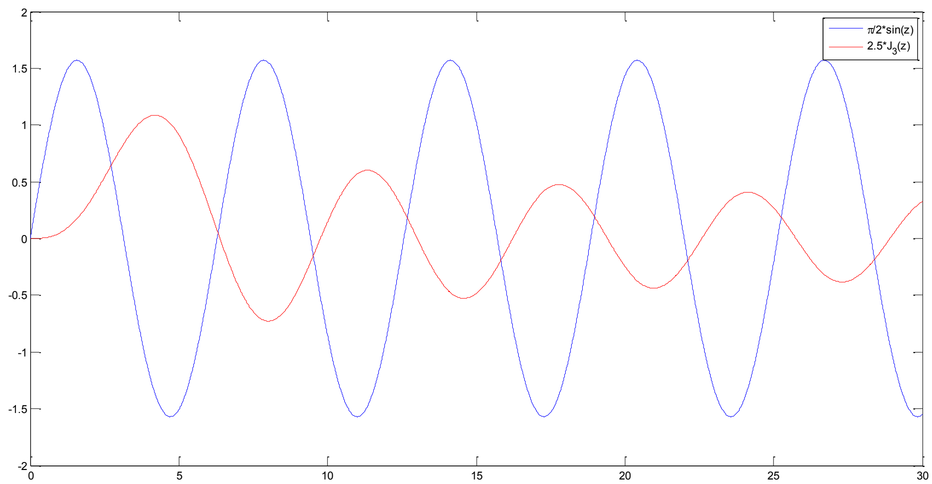

Figure 1: Graph of Sin(x) and Bessel function of 3rd kind

We have selected Bessel function because they behave like damped sine and cosine curves and stabilize over a longer period of time. In the starting of the simulation agents have high potential to perform the task but as time passes energy level will be low down. The third order Bessel function J_3 was selected empirically as it gave better values of DOL and QOW compared to J_1, J_2. We attribute this to the lower amplitude and flatter nature of the curve associated with J_3 as shown in Fig. 2. The values of the scaling factors $a_3 = 2.5, b_3 = 4.2$ were chosen for our model to maintain the genetic pull between $[0,1]$.

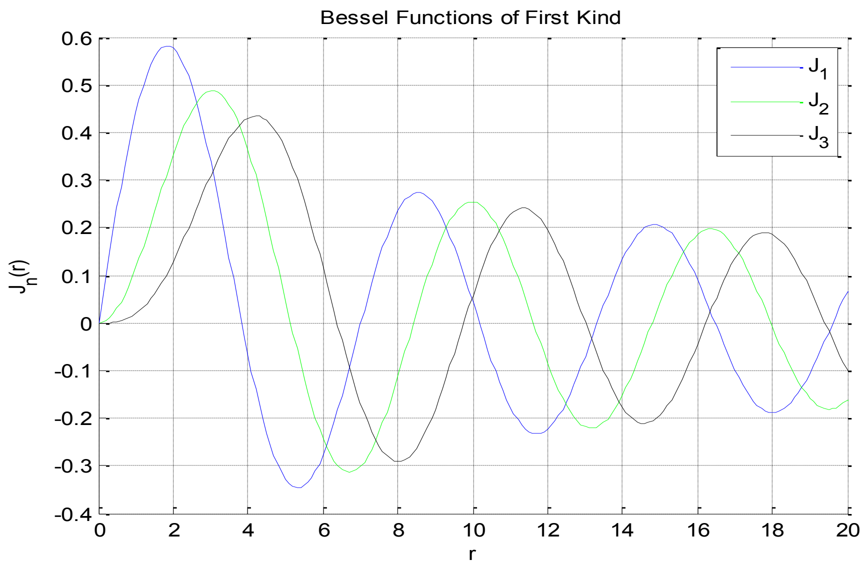

Figure 2: Graphs of various Bessel function of first kind

The third order Bessel function J_3 was empirically selected instead of J_1, J_2 as it improved values of division of labor while maintaining an upper edge over the quality of work compared to model in (Cockburn & Kobti, 2012). We attribute this to the lower amplitude and flatter nature of the curve associated with J_3. The Figure 3 represents the graphs of the genetic pull governed by equations (2) (dashed line) and (3) (smooth line), taking the value of MT = 1. From Figure 3, we see that the genetic pull controlled by equation (3) has higher values than the one given by equation (2). As a consequence of this, we expect a better level of specialization which is indeed achieved.

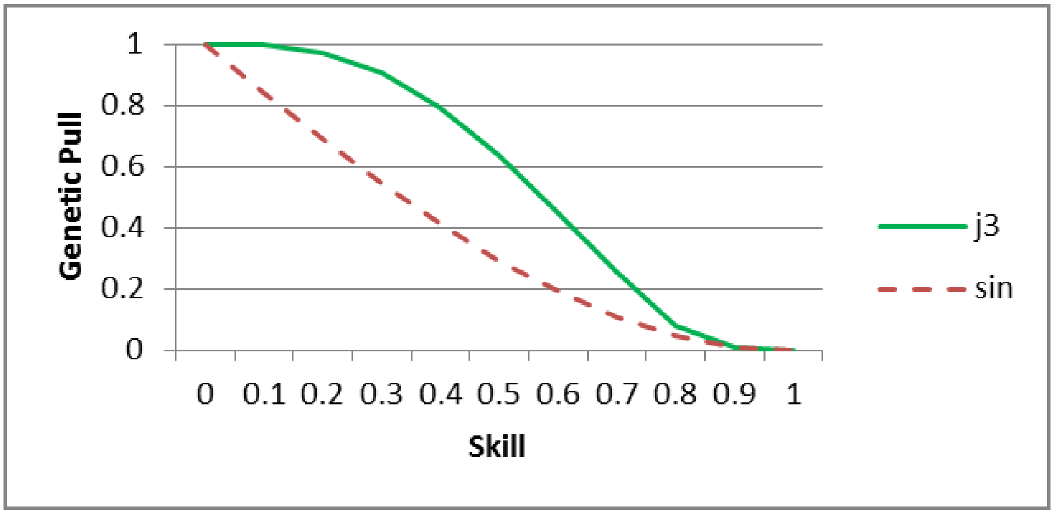

Figure 3: Genetic pull vs. Skill level

3.4 Stimulus Intensity

Each time a task j is performed by an individual, the stimulus intensity S_j, is decreased by an amount $\alpha = 3$, (same as in (Jeanson, Fewell, Gorelick, & Bertram, 2007)). For each time step, the level of the stimulus S_j, associated to task j is increased by:

$$\beta_j = \alpha \frac{N}{T} \delta \tag{4}$$

where, N is the group size (number of individuals), T the task number and δ the demand. Demand represents the total colony effort required to complete all tasks relative to the available total effort from workers. In (Jeanson, Fewell, Gorelick, & Bertram, 2007), the authors fixed the demand for all tasks thus; the rate of stimulus regeneration is identical for all tasks and does not vary over time.

We believe this is not very realistic so we let the rate of stimulus regeneration vary over time. This is achieved by considering the demand δ varying continuously over a smooth curve as shown in Figure 4. The curve is generated by using the following formula:

$$0.5 + 1.2J_3\left(\frac{25t}{1000} - 2\right) \tag{5}$$

where t is the simulation time step. Each simulation lasted 1000 time steps. The change in demand, in general, is oscillatory in nature and stabilizes over a longer period of time. This motivated us to choose the formula (5) for varying the demand with time satisfying both the requirements.

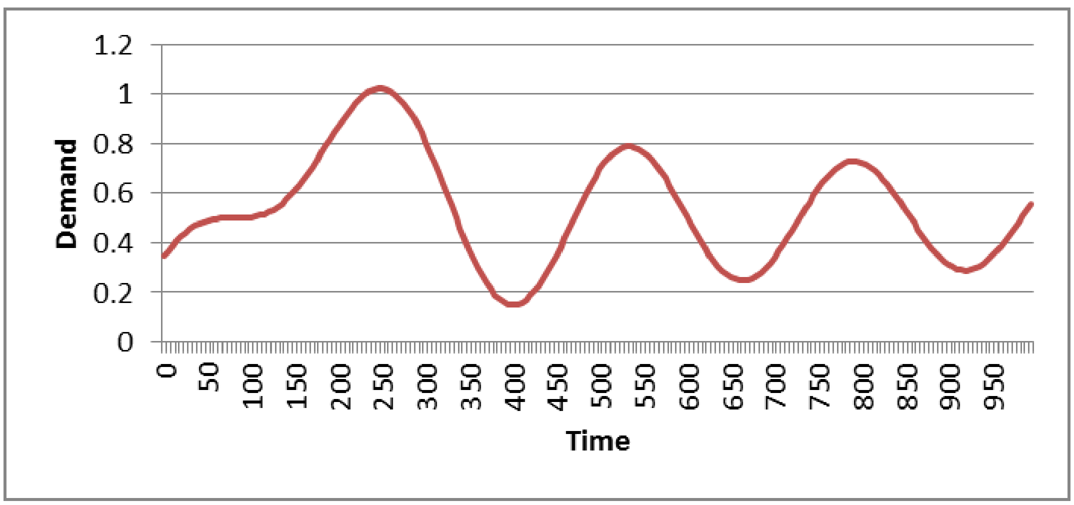

Figure 4: Demand vs. Time

This continuous choice of demand has the advantage that in each time step, the stimulus changes thus depicting the real world more accurately. We then choose demand randomly in (0.1, 1.1), for each task. In this case each task has a different stimulus which was omitted for simplicity in (Jeanson, Fewell, Gorelick, & Bertram, 2007).

Further to compare our results with that of (Jeanson, Fewell, Gorelick, & Bertram, 2007), we choose the same discrete values of δ as in (Jeanson, Fewell, Gorelick, & Bertram, 2007).

3.5 Experiments and Results

3.5.1 Design of experiments

The main focus of this section is to design experiments to observe the influence of (i) demand $\delta = 0.7, 0.9, 1.0, 1.1$, (ii) demand chosen randomly in (0.1,1.1) and (iii) demand varying continuously over the smooth oscillatory curve of figure (4); on DOL and QOW.

A metric to measure level of specialization within a population was developed by (Gorelick, Bertram, Killeen, & Fewell, 2004). We use the same metric to measure DOL. The measure quantifies the degree to which agents in a population are specialized. We have each agent record their task allocation amounts. These amounts are then stored in an $n \times m$ matrix, where n is the number of agents and m is the number of tasks. We then normalize this matrix such that the sum of all cells is 1. The mutual information and Shannon entropy index (Shannon., 1948) are then calculated for the distribution of individuals across tasks. Finally, dividing the mutual information score by the Shannon entropy score will provide a value between 0 and 1. A score of 0 indicates a population with no specialization and a score of 1 indicates a fully specialized population (Gorelick, Bertram, Killeen, & Fewell, 2004).

We use the metric developed by (Cockburn & Kobti, 2012) to measure quality of work (QOW). It is a measure of the average amount of skill used in performing a task. The quality of work is a value between 0 and 1. A higher value indicates that the task was performed by a more skilled agent. All the agents are assigned an average skill level of 0.5.

Agents will perform one of tasks that cross its thresholds or be inactive if no such task exits. Each individual was given a uniformly random initial threshold value for each task between 0 and 3, which served as our maximum thresholds. Each agent was also given a random skill level between 0 and 1 for each task.

Simulations were run for 100 times for each combination of the parameters. The models were compared across several combinations of tasks and agent counts. Similar to the original paper, we tested with 2, 4, 10 and 20 tasks and 10, 50, 100, 500 and 1000 agents. For each combination, we measured the resulting level of division of labor (DOL) and quality of work (QOW). The average values were then considered for a particular combination. The results are illustrated in the Figures 5-10. Each graph illustrates the values of DOL and QOW for the genetic pulls governed, respectively, by sin curve and by the proposed Bessel curve. The Y- axis of each graph presents the value between 0 and 1. The X- axis represents each level of agent count that we used.

3.5.2 Comparison with existing model

In this section, we compare the level of specialization between our model and the one proposed in (Cockburn & Kobti, 2012). The effect of our new formula (3) for genetic pull is reflected in the Figures 5-8, where J_3 (diamond) and $\sin$ (square) represent DOL from our model and from the one proposed by (Cockburn & Kobti, 2012). We get better values of DOL as compared to (Cockburn & Kobti, 2012). There is a general increase in the level of specialization as the agent count increases and also as the number of tasks increase.

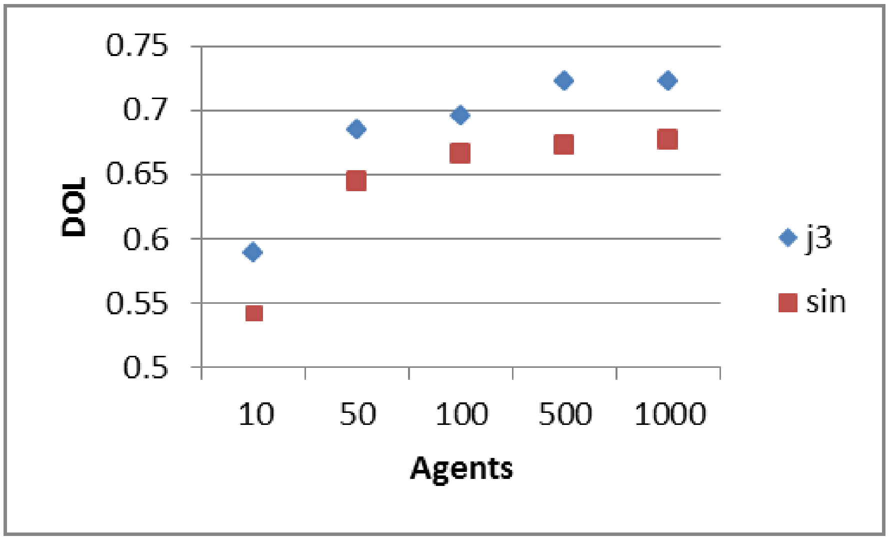

Figure 5: DOL with 2 Tasks

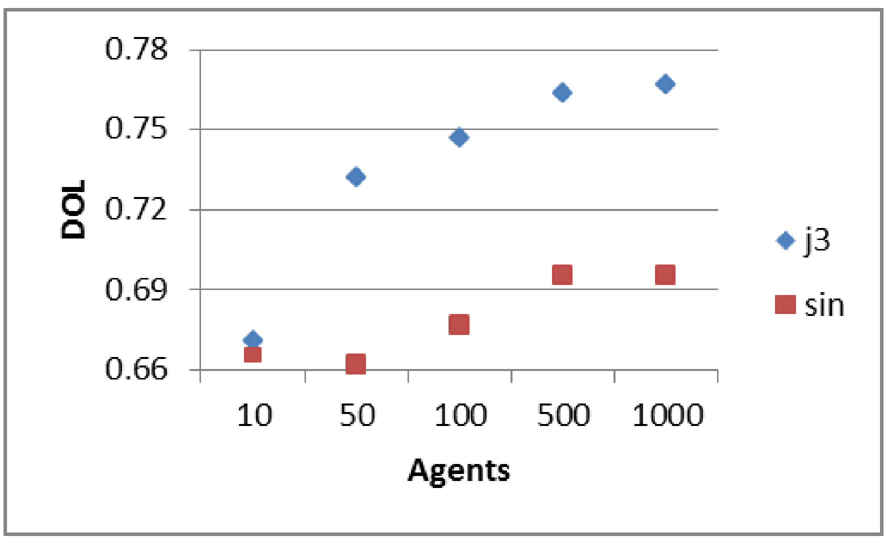

Figure 6: DOL with 4 Tasks

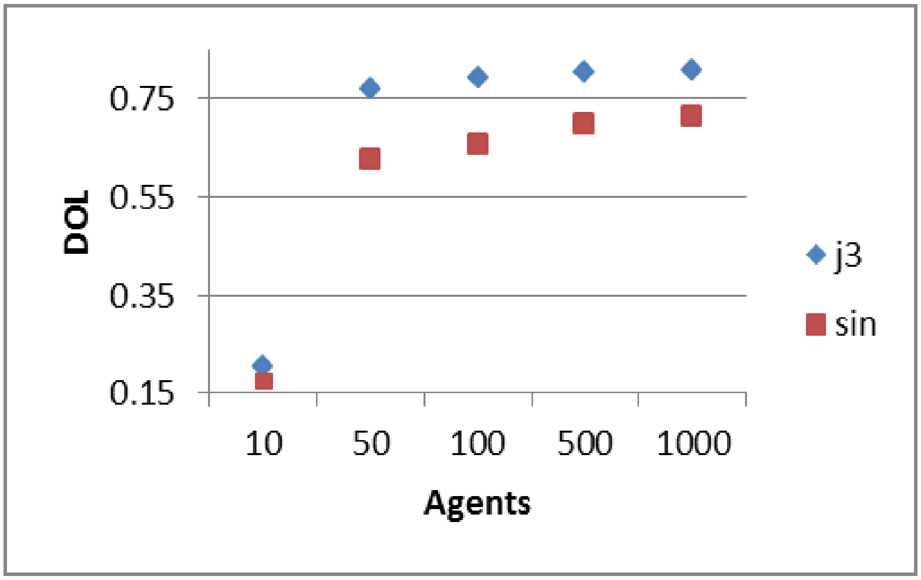

Figure 7: DOL with 10 tasks

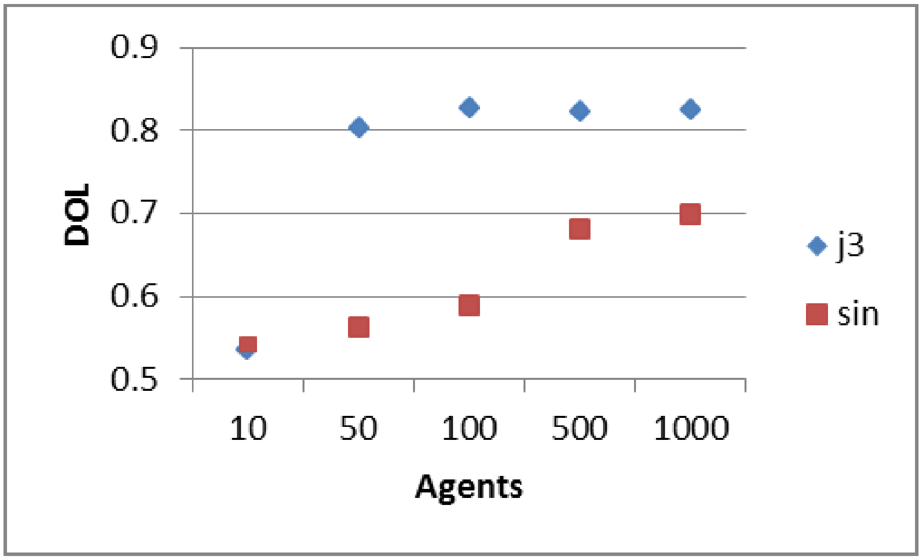

Figure 8: DOL with 20 Tasks

In our model DOL always increases with increase in task count except when the number of tasks and agents were equal. The QOW is similar in the models proposed by us and in (Cockburn & Kobti, 2012), and hence was omitted from the results.

3.5.3 Discrete Demand

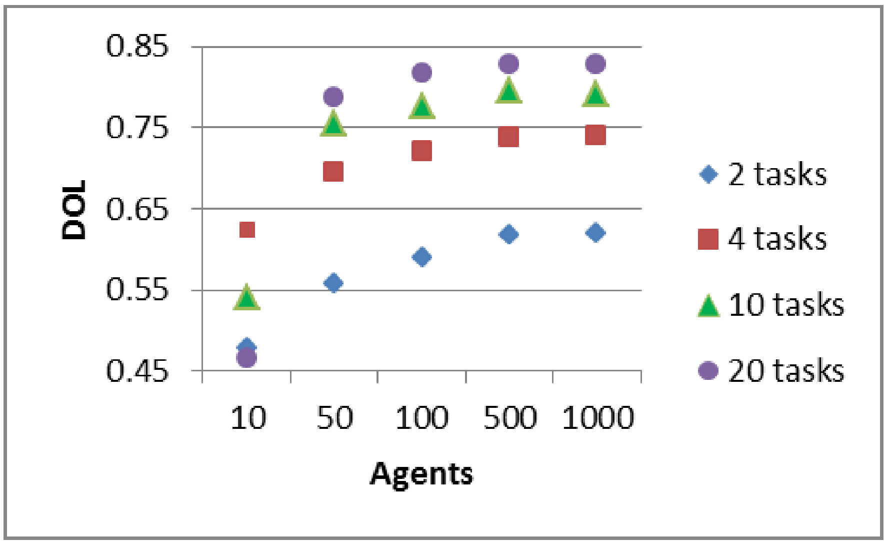

Figure 9: DOL with δ = 0.7

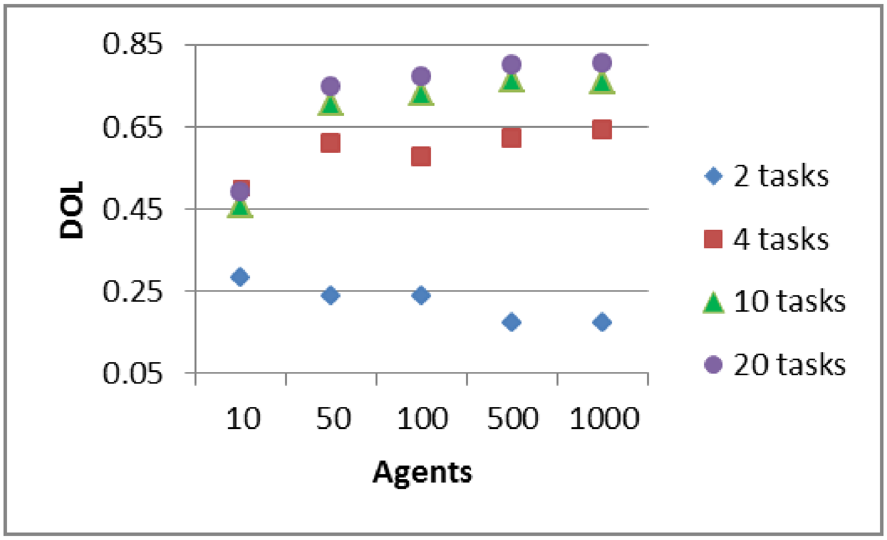

Figure 10: DOL with δ = 0.9

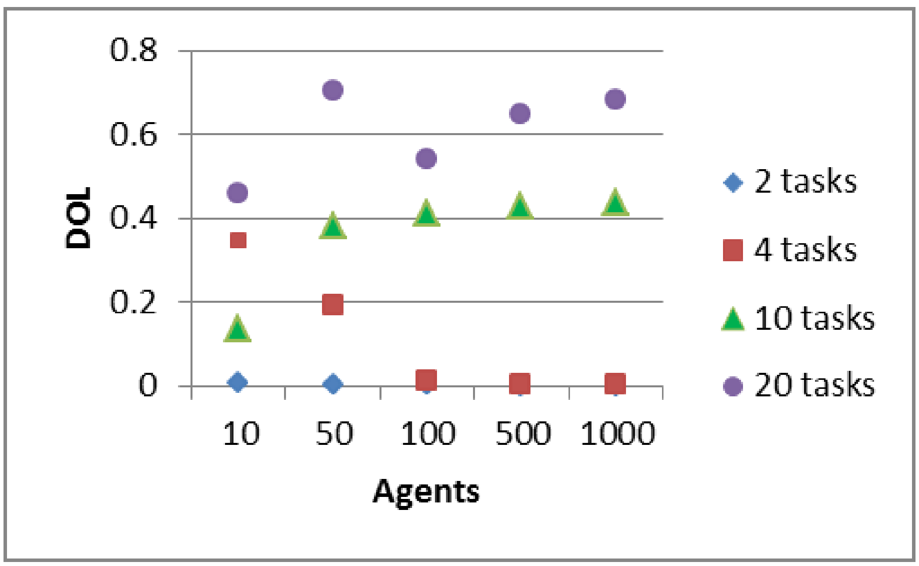

Figure 11: DOL with δ = 1.0

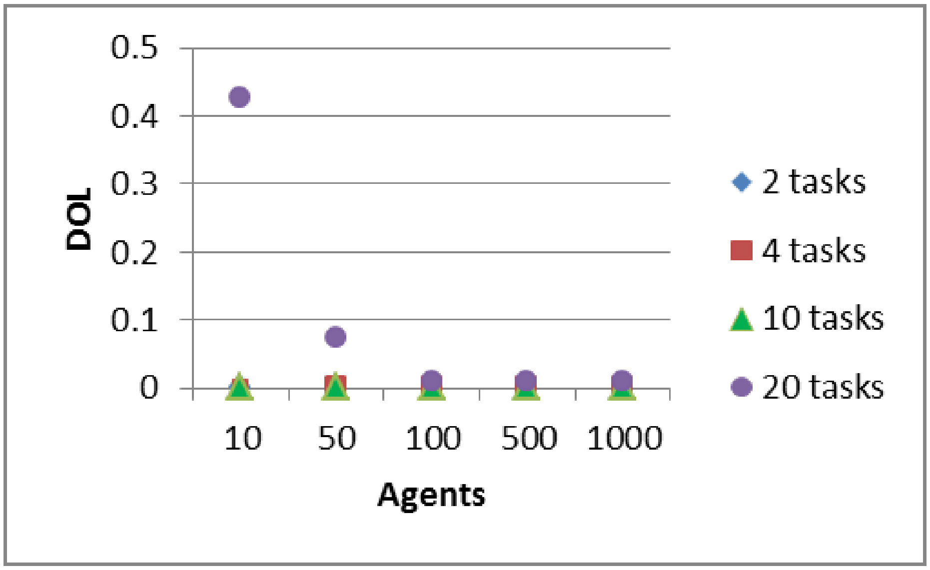

Figure 12: DOL with δ = 1.1

For $\delta = 0.7$, DOL increases with group size for all tasks and for groups size 50 or more it increases with number of tasks. As demand increases to 1, DOL decreases with group size for 2 and 4 tasks. For $\delta > 1$, DOL drops as expected.

3.5.4 Random Demand

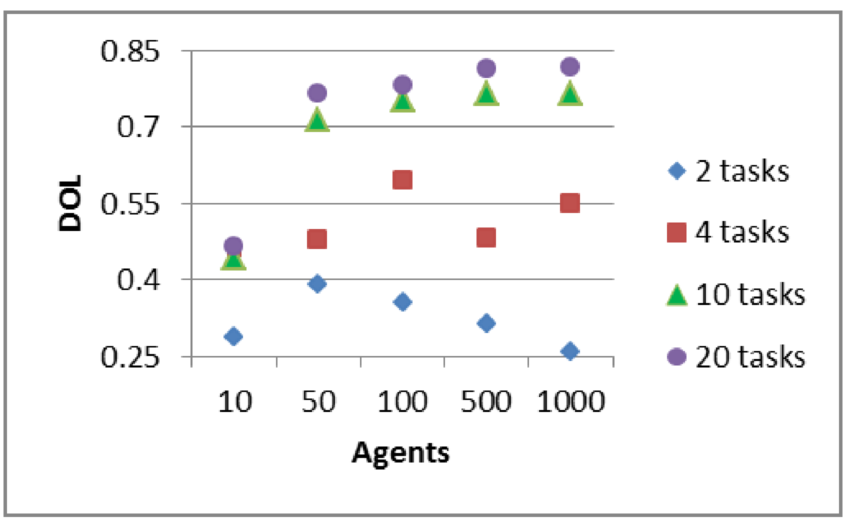

Figure 13: DOL with random demand

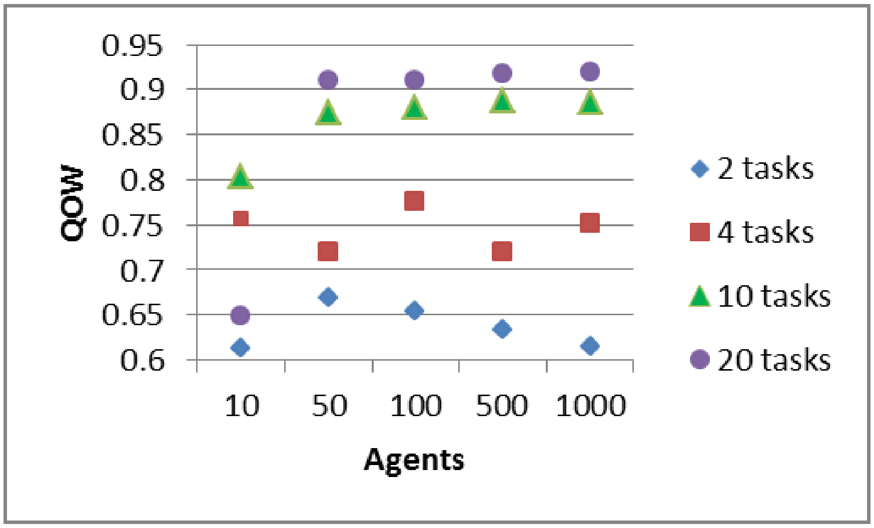

Figure 14: QOW with random demand

The level of specialization increases with tasks for random demand. For 10 and 20 tasks, the DOL increases with agent count. For 2 tasks, DOL increases with agent count till 50 agents and then starts decreasing with agent count. For 4 tasks, DOL oscillates between 0.45 and 0.6. The QOW follows similar pattern.

3.5.5 Continuous Demand

The level of specialization increases monotonically with group size, except for 4 tasks, where there is a dip in specialization level for 10 agents. For all tasks the DOL stabilizes around 500 agents while QOW stabilizes around 50 agents. For population less than 50 agents, the QOW decreases with increase in task number.

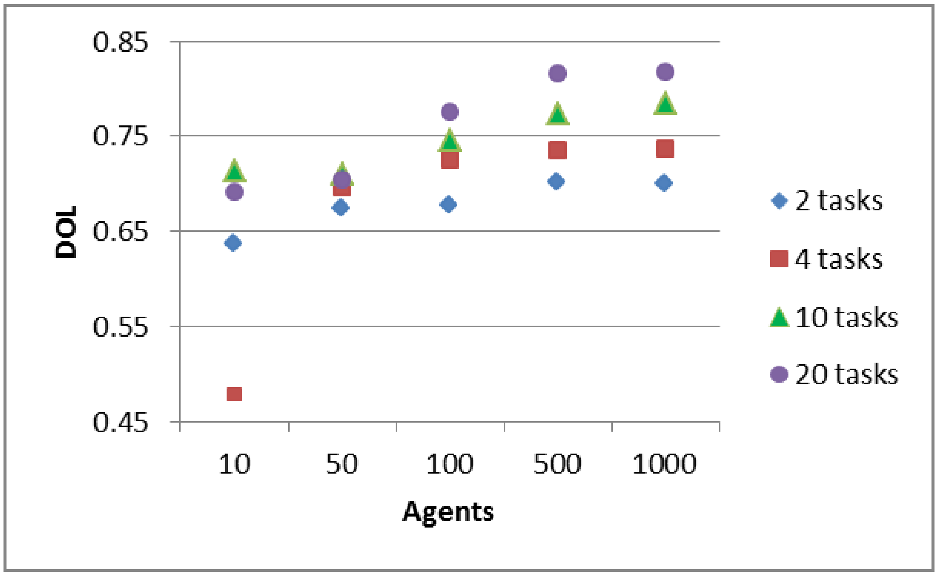

Figure 15: DOL with continuous demand

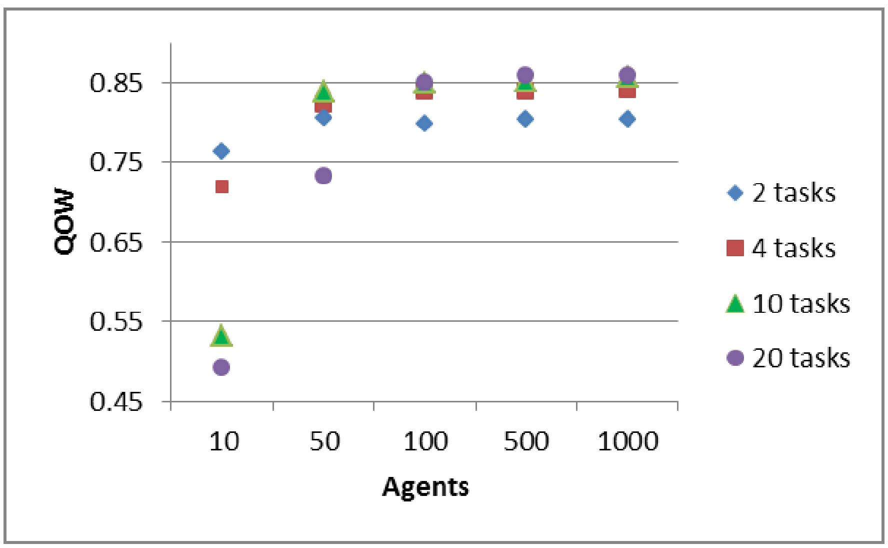

Figure 16: QOW with continuous demand

3.6 Discussion

In the proposed model, specialization is influenced by number of agents, task number, and demand. There is interplay between these three parameters. The effect of task number and group size on DOL varies as demand moves above or below one. When demand is greater than one, from Eq.(4), we see that the stimulus intensity of each task rises quickly above the threshold of any agent so that all agents become equally likely to perform any task at each time step, regardless of thresholds. Hence, there is no proper division of labor (Figure 12). For demand equal to one, division of labor actually decreased with increasing group size for 2 and 4 tasks but it increased with group size for 10 and 20 tasks as illustrated by Figure 11. When demand level is below 1, agents have fewer specializations that will have enough stimuli to surpass their thresholds. The results indicate that even when there is low demand, enough agents are still faced with multiple choices, resulting in a specialization from social influence. The role of a high task number for DOL is less if task number is 4 or more.

From the Figures 5 to 8 we noticed significant increases in division of labor in the new model compared to (Cockburn & Kobti, 2012). The specialization increases monotonically with group size for 2 and 4 tasks whereas for 10 and 20 tasks, the DOL increases initially with group size and almost stabilizes for groups of size 100 or more.

The Figures 9 to 16, showing all the three cases of demand, implies that continuous demand is the best followed by random demand and then discrete demand at the bottom. QOW also follows the similar pattern in all the three cases.

3.7 Conclusion and Future work

We have proposed a new hybrid model by introducing a new formula for genetic pull. This helps to increase the DOL as compared with the model proposed by (Cockburn & Kobti, 2012). The QOW is either slightly better or at par with QOW achieved in (Cockburn & Kobti, 2012).

The novelty of our approach is that we analyze the DOL and QOW by introducing the concept of continuous and random demand in our model. The demand changes depending on several factors like colony size, climatic changes across social systems as well as other biological systems. Assuming the food is the resource in an ant colony, its availability is higher during summer thus reducing the demand and consequently during winter demand is higher owing to scarcity of food. Hence demand is oscillatory in nature. Over a longer period, the colony also tries to preserve some food for leaner periods, hence the demand eventually stabilizes. Keeping these requirements in mind, we constructed formula (5) for the demand, which is both oscillatory and eventually stabilizes around a point.

The increase in the DOL with group size, as shown by Figures 5 to 8, is in conformity with (Karsai & Wenzel, 1998) and (Thomas & Elgar, 2003) who concluded that an increase in division of labor could parallel an increase in group size directly via the distribution of thresholds within groups and indirectly via by-products of increased group size (i.e. task number and demand).

There is a marked difference in DOL and QOW for random demand compared to continuous demand. In the random case, both DOL and QOW are heavily task dependent. These are better for higher number of tasks as compared to fewer tasks.

In the future work we will focus on a combination of our continuous and random approaches such that demand for each task varies continuously on a randomly chosen smooth curve.

CHAPTER 4

Positive Social Response in Modeling Adaptive behavior of the industry cluster

4.1 Preface:

Adaptation helps the individual organization to adjust its behavior so as to achieve healthy growth of both the individuals and the whole industry cluster as well. In this chapter, we propose a new Industrial cluster model adaptation based on two new concepts: (i) The Score function f_t, a parameter depending on the positive social influence and (ii) a new formulation for the work load $\gamma_{x,j}(t)$ (of an organization x for the task j at time t) depending on the stimulus intensity $S_{x,j}(t)$ via the Bessel function J_3. The model is tested through numerical simulation for the emergence of specialization in the cluster.

4.2 Introduction:

Industry clusters is a group of some interactive relevant enterprises, specialization suppliers, service providers, financial institutions, relevant industrial manufacturers and other related organizations with all these members of the group settling in a special region. They cooperate as well as compete with each other. Clusters are used to increase the productivity with which companies can compete, nationally and globally. The main idea of clusters was introduced by (Porter, 1998). Porter claims that clusters have a capability to increase the productivity of the companies in the clusters. According to his findings in “The competitive advantage of nations”, he concludes that companies gain advantage against the world’s best competitors because of pressure and challenge.

Companies achieve competitive advantage through acts of innovations involving not only new technologies but also adopting new ways of doing the things. According to him, clusters are concentrations of highly specialized skills and knowledge, institutions, rivals, related business, and sophisticated customers in a particular nation or region (Porter, 1998).

There are several examples of industrial clusters. Some of the famous examples of clusters are Guangdong, Jiangsu, and Zhejiang in China and Silicon Valley in USA. The cluster plays an important and strong role in regional economy. According to statistics, more than a third of its total industrial output value is produced by the current characteristic of industrial clusters in industrial output in Zhejiang province of China (Yang & Niu, 2013).

Industrial cluster analysis is a better way to understand our regional economy. The purpose of clusters analysis is to identify those areas of the economy in which a region has comparative advantages and to develop short and long term strategies for growing the regional economy (Albino, Carbonara, & Giannoccaro, 2008). An industry cluster is considered to have comparative advantages if the output, productivity and growth of a cluster are higher relative to others in the region. Shared geographic locations and common goals are two factors for the development of industry clusters. Workers, inventors, institutions such as government and education, and others support the clusters and affect a broad range of industry clusters grouping (Albino, Carbonara, & Giannoccaro, 2008).

Common goals and geographic concentration lead to the development of specialized skills, institutions, and alliances within the cluster agglomeration. Normally, there are neither official guidelines nor standardized definitions for industry clusters, each of the potential emerging cluster must be analyzed case by case in order to determine whether or not they exist in the region (Albino, Carbonara, & Giannoccaro, 2008).

Economic globalization has lead to the world where specialization or division of labor plays a major role in the development and success of the industrial clusters. In the global division of labor, the industrial cluster is a common industry approach and strategy selection in the world of regional economic development (Yang & Niu, 2013).

The name cluster is very popular in several fields but it came naturally from insect's colony (Wei & Feifan, 2009). Hence it is quite useful to use some swarm based approach to solve these types of problems. As it is known, industrial clusters effectively promote regional economic development in the way that it makes the regional economic integrate into the world so as to participate in the global division of labor markets and expand the global competition and collaboration (Wei & Feifan, 2009).

According to (Maynard Smith & Szathmary., 1995) division of labor (DOL) is the one of the most basic and widely studied aspects of colony behavior in social insects. Division of labor, in which different workers specialize on subsets of the tasks performed by a colony, is one of most prominent feature of social insect colony. Division of labor is fundamentally a stable pattern of variation among workers within colony in the tasks they perform. More precisely by saying that each worker specializes on a subset of the complete repertoire of tasks performed by the colony and this subset varies across individual workers in the colony.

Division of labor or specialization is one of the primary attributes of sociality. Caste and specialization have been the focus of the study of the organization of insect societies for more than fifty years. Indeed, the description and analysis of task allocation between colony members are fundamental to understand the organization of a complex biological system whose functioning depends upon the behavioral integration of a potentially large number of individuals or agents. The advantage of specialization by individuals within groups is also considered to be of overwhelming importance in many of the major transitions in the evolution of life (Maynard Smith & Szathmary., 1995).

Specialization is allocating a disproportionate amount of a resource to one task compared to other available tasks (Spencer, Couzin, & Franks, 1998). In population of heterogeneous individuals, it is often the case that these individuals possess different aptitudes for available tasks. Individuals increase their productivity by enhancing their specialization in communities of mutual interest, whereby other individuals are also trying to maximize their productivity in relation to competitors.

There are several different ways to cause the emergence of specialization within a complex system. The agents may choose their specialization or it may be assigned as is the case in caste system. Several factors including genetic, social and economic considerations affect the choice of specialization (Singh, Shah, & Kobti, 2013).

Several genetic models have been proposed for the study of specialization. The most widely used are the response thresholds model. The thresholds model presents a certain level of stimulus for each task at which an individual will choose to specialize in that task (Theraulaz, Bonabeau, & Deneubourg., 1998). In the threshold model, agents by default perform no tasks. It means if there is no stimulus for any of the possible tasks, then individual will do nothing. Agents will also perform no tasks if none of the stimuli for all available tasks fail to cross its response threshold. The threshold varies between agents.

In some approaches, performing a task causes the thresholds level for that task to decrease, while not performing the task will lead to the thresholds level increasing (Beshers & Fewell, 2001) and (Singh, Shah, & Kobti, 2013).

A single enterprise/organization in an industry cluster owns all the properties such as autonomy, interaction and environment. Now from the macroeconomic view, any individual enterprise/organization in an industry clusters can be called as agent (Albino, Carbonara, & Giannoccaro, 2008). Every individual enterprise/organization in a cluster is an agent with some intelligence (Albino, Carbonara, & Giannoccaro, 2008). The main idea behind this paper is to propose a simple industry cluster model by using the properties of multi agent system and analyze the problem through simulation. The model is based on assumption that all the individual organizations are approaching for a common goal. The goal is to perform the task. In our simulation we assume that there are set of tasks and each organization can perform some of these tasks successfully.

In this chapter, we propose a model having attributes of a social network. There are several types of social network depending upon the uses and requirements of the problem. Normally social network is a social structure consisting of related items. As the name suggests, networks are like graphs where node represents an entity and edge represents a relation between the nodes. Family relationship is also a kind of social network, where edges connect two relatives. The small world network concept was given by (Milgram., 1967), and according to him all humans/agents in similar network are related via shortest paths of acquaintances. The application of small world is common to many research fields like World Wide Web, business process, railway track etc. It also includes the famous 6 degree separation, the concept is anyone can be connected to any other person through a chain of acquaintances that has no more than five intermediaries (Milgram., 1967). There are so many models which are influenced by the small world network, each having different characteristics and limitations. Each Organization in the industry cluster is represented by a node in small world network. In this paper, we propose a model of an industry cluster based on the concepts of positive social response, work load and consequent to these the emergence of cooperation among the organizations in modeling its adaptive behavior and show how specialization evolves in the cluster. Specialization is one of the key factors that improve the productivity of the cluster.

In next section of the paper we discuss the main functionality of our model. We basically analyze the effect of: 1) positive social influence, and 2) workload; influencing the individual organization to select a task. We discuss why positive social influence is important for individual organization to pick a certain task. When the workload of an organization increases, it becomes counterproductive and to overcome this problem, cooperative behavior from the other organizations in the cluster is needed. So, cooperation within the organizations plays an important role in DOL/ specialization in the cluster. It is obvious that if there is cooperation then straight away there is competition as well.

4.3 Industrial Cluster Model

In this model, the above two factors, playing crucial roles for individual organization to select multiple task from the given available options in the industry cluster, are incorporated. The first factor is the positive social influence which motivates individual organization to pick the task that several of its neighbors are performing. Initially agent selects tasks at the beginning of the simulation with none of them inactive. According to classical genetic thresholds model, agent will perform no task if none of the stimuli for all available tasks fail to cross its response threshold. In the standard genetic thresholds model, an agent selects a random task out of all the available possible tasks for which the stimulus for the task crosses its response threshold. In our formulation we believe that positive social influence plays a vital and important role in selecting a task. The decision of an agent to select tasks will be influenced by his neighbor's decision. Agent will not consider those neighbors which are inactive.

In the following, T and O will denote the sets of available tasks and the organizations. The number of tasks in T and the number of organizations in the cluster are denoted by M and N , respectively. For a given task $i \in T$ and an organization x , $N_{x,i}(t)$ is the numbers of organizations (other than x) that are engaged in task i at time t. The metric $d(x, y)$ is the path length between the organizations x and y (treated as nodes x and y in the network). Let $N_{x,i}^{d}(t)$ denotes the number of organizations engaged in the task i at time t separated from x by a distance d. Then

$$N_{x,i}(t) = \sum_{d\geq 1} N_{x,i}^{(d)}(t) \quad (1)$$

For an organization x in O and a task $i \, \varepsilon \, T$, we define a function $f_t: O \times T \rightarrow R_+$ as

$$f_t(x,i) = \frac{\alpha_i N_{(x,i)}^{(1)}(t)}{\sum_{j \varepsilon T, j\neq i} \alpha_j N_{x,j}(t) + M} \quad (2)$$

Where R_+ is the set of positive real numbers. The function $f_t(x, i)$ is called the "Score" of the organization x for task i at time t. The Score is the measure of the cumulative strength of the positive social response from the immediate neighboring organizations.

Normally, the score lies in [0,1]. The score >1 signifies that the majority of organizations are involved in task i at the given time t and the number of tasks M is $\ll N_{x,i}(t)$. The parameter $\alpha_j, j \in T$ is the weight assigned to the task j. From all the available tasks, the organization x will pick a task according to its Score for that task obtained from Eq. (2). The task with the highest Score will be selected by the organization x. The weight α_j is an indication of the measure of the strength of the positive social influence for the task j.

In an insect colony or artificial agent society or even in human society the impact of positive social influence is important to take into account. The effect of positive social influence on DOL is analyzed by choosing different values of the weights α_j in Eq.(2). If positive social influences of neighbors are high then they motivate organization to pick task they are involved with. For simplicity, all weights α_j are assigned the same values in the numerical simulation to study the specialization. In our simulation, we assume that all agents have the same level of influence. However this is not required, it is also possible to take different values for different agents, but for simplicity, we assume the same level of influence. We can also create the effect of age polytheism if we were to have the influence rate grow with age.

Besides the score $f_t(x,j)$, the stimulus intensity $S_{x,j}(t)$ is also a driving force for an individual organization x to select a task j. The more the stimulus, better is the chance for the task to be selected. Hence, once a task j is selected by x, $S_{x,j}$ should be decreased by a certain amount β. As long as the task j is not selected, the level of stimulus $S_{x,j}$ will increase at each time step according to

$$S_{x,j}(t+1) = S_{x,j}(t) + \beta \frac{N}{M} \delta \quad (3)$$

Where δ is the demand. Demand represents the total cluster effort required to complete all tasks relative to the available total efforts from organizations.

In this model, we propose the work load $\gamma_{x,j}(t)$of the organization x at time t with respect to task j. The organization work load $\gamma_{x,j}$ is used as a feedback for computing the response threshold $\theta_{x,j}$, allowing $\theta_{x,j}$ increasing when work load is high. This reduces the probability to select the task j. This will ensure that when individual organization is busy, it will not accept any tasks; otherwise, if it is free, it can easily take task. We propose the following formula to compute the work load.

$$\gamma_{x,j}(t) = \theta_j[1 - J_n(S_{x,j}(t)] \quad (4)$$

where θ_j refers to the maximum threshold of an organization x which can possess for the task j, and j_n is the well-known Bessel function of first kind and of order n. In numerical simulations we take $n = 3$ as it gives better result for the same reasons as explained earlier in chapter 2. If individual organizations x in the meantime want to select the same task j again then it is important to know the current status of organization x for the previously doing task j. This is only possible by keep tracking of updated value of response thresholds. Now, $\theta_{x,j}(t)$ is updated as

$$\theta_{x,j}(t+1) = \theta_{x,j}(t) + \gamma_{x,j}(t) \quad (5)$$

When an individual organization cannot finish the task, possibly due to workload, the cooperative behavior is required among the cluster. The cooperative behavior is observed in insect's colonies. Ants are able to pick large piece of food but it is not possible for a single ant to carry it. So, the ant will produce pheromones to attract others to follow her path and cooperate in carrying the large chunk of the food. The same concept is also observed in bee's society where scout bees, being sent in to search for promising flower patches, move randomly from one patch to another. When they return to the hive, the scout bee, that found a patch rated above a certain quality threshold, perform a typical dance known as waggle dance to recruit the other bees. In the business world also sometimes, it is not possible for one organization to become specialized in one of the tasks; they need support from others to survive. So if any individual organization who is suffering from task workload needs help from other organization in the cluster then emergence of cooperative behavior comes from their neighbors in the cluster. There are two ways to achieve this adaptive behavior in the model:

1) The organization seeks cooperation from the distant neighbor (separated by a distance >1) to increase its cumulative score when the Score for the task is low as obtained from Eq. (2). The organization x increases its Score for the task i from cooperation by the other organizations in the network by taking into account the social influence of the organizations which are not immediate neighbors of x. In the proposed model, the cooperation to the organization x from the positive social influence of the organizations y, which are separated from x by distance greater or equal to 2, is also added to increase the Score of x for the task i, thereby inducing the organization x to take the task i. This is achieved by modifying Eq. (2). The additional terms coming from the positive social

influence of organization y are added in the numerator. Thus, we propose the following formula for the cumulative Score:

$$f_t^c(x,i) = \frac{\sum_{d\geq 1}\frac{\alpha_i}{2^{d-1}} N_{x,i}^{(d)}(t)}{\sum_{j\epsilon T, j\neq i}\alpha_j N_{x,j}(t)+M} \qquad (6)$$

We illustrate our formulation through the following very simple graphical example of an industry cluster. It shows that how individual organizations are connected in small world network. If at any time individual organization x wants to select any task then it will calculate cumulative score on the basis of Eq. (6). Though the values of Score for task 1 and task 2 are 0.143 and 0.5 for the organization x (on the basis of Eq. (2)) respectively, the cumulative Scores are much higher as shown below.

Cumulative Score of Task 1: $f_t^c(x,1) = \frac{1+0.5\times 2+0.125\times 1}{5+2} = 0.3036$

Cumulative Score of task 2: $f_t^c(x,2) = \frac{3+0.5\times 1+0.25\times 1}{4+2} = 0.625$

(the value of α is 1)

In the given below graph, each rectangle represents one individual organizations.

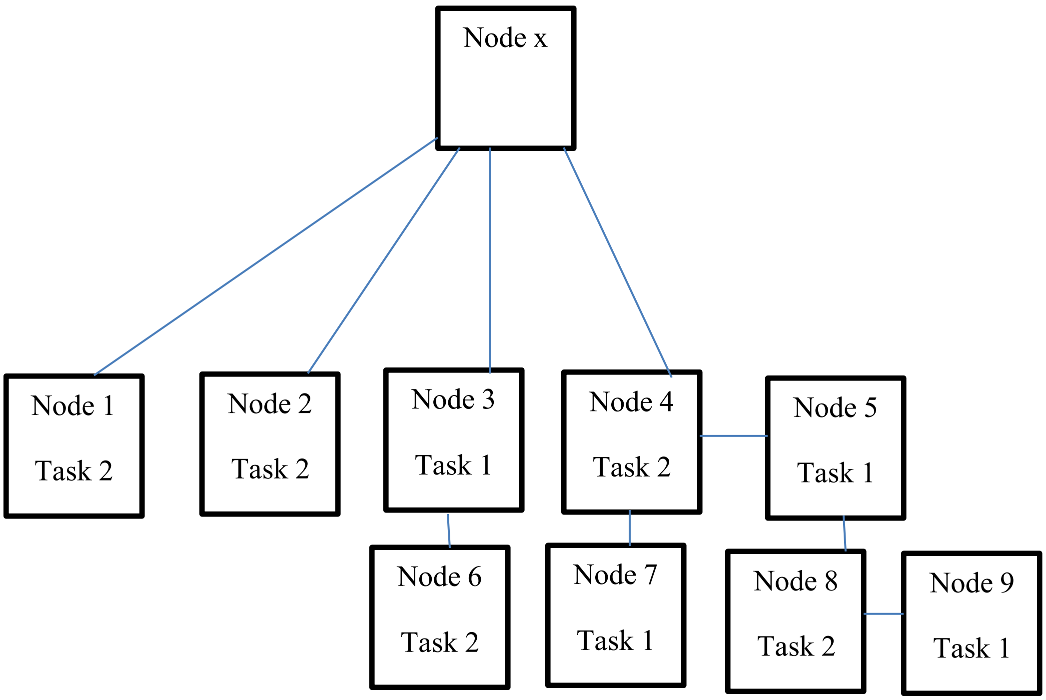

Figure 1: Graphical representation of an industry cluster

2) Let $\hat{\theta}_{x,i}(t)$ be the critical threshold of the organization x to select the task i . If the organization x is not able to select the task i due to workload, besides increasing its score to cumulative Score, it seeks cooperation from the other organizations to reduce its current threshold $\theta_{x,i}(t)$ for the task i to its critical value $\hat{\theta}_{x,i}(t)$, enabling the organization x to select the task i, through the following formula

$$\hat{\theta}_{x,i}(t) = \theta_{x,i}(t) - \sum_{d\geq 1} \frac{\theta_{y_{d,i}}(t)}{2^{d-1}} \quad (7)$$

where y_d is an organization which are doing task i in the cluster at a distance d from the organization x. The summation terminates as soon as $\theta_{x,i}(t)$ attains its critical value $\hat{\theta}_{x,i}(t)$.

4.4 Experiments and Results:

In this section, we apply the proposed industrial cluster model to see the emergence of specialization/DOL in an industrial cluster. A metric to measure the level of specialization within a population was developed by (Gorelick, Bertram, Killeen, & Fewell, 2004). We use the same metric to measure specialization level of individual organization in the cluster and compare it with standard genetic thresholds model. The measure quantifies the degree to which individual organization in a population are specialized. Each individual organization records its chosen task at the end of each of the iterations. The recorded information of all the individual organizations are then stored in a $N \times M$ matrix, where N is the number of organizations and M is the number of tasks. We then normalize this matrix such that the sum of all cells is 1. The mutual information and Shannon entropy index (Shannon., 1948) are then calculated for the distribution of individuals across tasks. Finally, dividing the mutual information score by the Shannon entropy score will provide a value between 0 and 1. A score of 0 indicates a population with no specialization and a score of 1 indicates a fully specialized population (Gorelick, Bertram, Killeen, & Fewell, 2004). A higher value indicates that the task was performed by a more skilled organization (Cockburn & Kobti, 2012). The better value of division of labor means that there is proper balance in the cluster. All the individual organizations are doing some task. It is not the case that some organization are doing the entire task while other organizations are sitting idle and doing nothing. If the division of labor is proper, it means all the organizations are busy in doing some task and none of them are inactive. If there is no proper division of labor, it causes recession in the cluster. The proper division of labor can improve performance level of individual organizations in the cluster and still the weaker organizations have chance to grow and prevent from debacle.

Each individual organization was given a uniformly random initial threshold value for each task between 0 and 50. We tested for 50, 100, 150 and 200 individual organizations and for the 10 and 20 tasks and compared our results with that of the GTM. The model was tested with different value of influence level to measure the impact on specialization. We took α_j = 0.5 and 1 in our ICM model to compare results between them.

Table 1: DOL with 10 Tasks

10 Tasks	50 Organizations	100 Organizations	150 Organizations	200 Organizations
GTM	0.46	0.51	0.53	0.57
ICM = 0.5	0.49	0.53	0.59	0.61
ICM = 1	0.55	0.58	0.63	0.71

Table 2: DOL with 20 Tasks

20 Tasks	50 Organizations	100 Organizations	150 Organizations	200 Organizations
GTM	0.54	0.59	0.65	0.71
ICM = 0.5	0.58	0.67	0.69	0.77
ICM = 1	0.63	0.73	0.79	0.91

Table 3: DOL with 20 tasks

20 Tasks	50 Organizations	100 Organizations	150 Organizations	200 Organizations
ICM	0.63	0.73	0.79	0.91
ICM without cooperative behavior	0.52	0.64	0.74	0.85

The Table 3 shows the superiority of the ICM with cooperation over the ICM without it.

4.5 Discussion:

We compare our model with the classical genetic thresholds model. From the table 1, 2 and 3, it is clearly seen that results obtained from our model is better than that from the genetic model. The higher value indicates that the task was performed by a more skilled organization and that there is a proper specialization in the system and all the individual organizations are doing tasks according to their skills and threshold values and none of them being inactive.

We claim that the positive social influence increases the specialization level in the cluster. In the positive social influence model, individual organizations are attracted by their neighbors and try to pick the same task for specialization. From the table 2, it is clear that better DOL is achieved when $\alpha = 1$ compared to when $\alpha = 0.5$. We can also take the value of α greater than 1 but we believe that this is not an ideal way to do so. Since higher the value of α, higher is the chances that organization's own decision will be overwhelmed by the positive social response from the neighbors. So our finding is that positive social influence increase the division of labor in the cluster or in a group while the previous finding focused on group size and task number.

The table 3 shows the effect of cooperative behavior. It is clear from the table 3 that cooperative behavior is necessary in the cluster to improve specialization and productivity. Cooperative behavior increases specialization because it gives a chance to those neighbors, who are sitting idle due to low capability to perform task alone, to take up that task.

4.6 Case Study:

The history of Silicon Valley is an excellent case study in terms of economic development and also gives a clear idea about industry cluster. Stanford University was the first educational institution to help regional and local area to grow and become stabilized. The university was opened in 1891. A dedicated team of professors, engineers, and professionals worked very hard to improve the university's reputations to attract the attention of qualified students. After successful support from the various government agencies, the private companies also started showing interest in the research and development projects of the university (Gore & Mhatre, 2009). Hewlett Packard's and Varian Associates opened new Stanford industrial parks, an office and research park on Stanford's campus to encourage the students and highly qualified professional to stay in there. The combined efforts culminated in various innovative ideas and technologies. Using these innovative technologies and companies as a catalyst, the area attracted a great deal of government funding, either directly to government institutions located in the area or to the private firms or schools there in (Gore & Mhatre, 2009).

The development and success of Silicon Valley is based on so many factors. Some of the important and crucial factors are the location of Stanford University, an efficient private management, and its highly qualified faculty dedicated to provide top class talented and well trained innovators to the development of industry cluster there in the area. Due to the strong social influence of the Stanford University, several universities and colleges helped the industry cluster in the region by opening their own research labs or by giving specialized training to their students according to the demands of skilled workers in the various industries. Some of the popular names of universities in the region are UC Berkeley, UC Davis UC San Francisco etc. These universities offered some specialized courses to cater the needs of the cluster. Thus this social influence wrote the success story of the Silicon Valley (Gore & Mhatre, 2009). So, we may justify our point that social influence increases the specialization resulting increase in productivity and thus improving the economic growth of the cluster. In our model, social influence is highly dependent on the distance or the type of network between different organizations. Universities near to the Silicon Valley or Stanford or California region follow the same trend due to strong social influence while the universities which are away in New York State have very little effect of social influence due to their large distance from the Silicon Valley clusters.

Educational attainment is another characteristic in which Silicon Valley is quite different from the national population. While only 24% of the US population has obtained a bachelors or post graduate degree, 40 % of the individuals of the Silicon Valley have achieved this level of education (Gore & Mhatre, 2009). This educated workforce is an important draw for employers in the area. We again claim our social influence factor here by analyzing such statistics. In Silicon Valley region, most of the students are opting for higher education to get good jobs. This motivates other students also in California region to follow the same trend due to positive social influence. The available data suggests that national average for higher education is for below the California average in conformity with the prediction of our model that positive social response decreases with increase in distance (Gore & Mhatre, 2009).

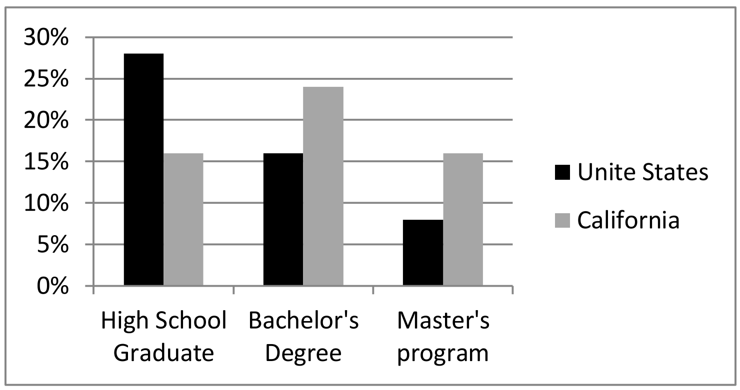

Figure 2: The national average for education verses the California average

4.7 Conclusion and Future Work:

The main contribution of the present work is that a new industry cluster model is proposed based on two new concepts of the Score function f_t measuring the cumulative strength of the positive social response and a new formulation for the work load $\gamma_{x,j}(t)$, of an organization x for the task j at time t depending on the stimulus intensity $S_{x,j}(t)$ via the Bessel function j_3. Through the numerical simulation in the experimental Sec. 3, it is shown that positive social influence increases the division of labor in the cluster. The emergence of DOL with group size and task number was shown in (Thomas & Elgar, 2003), (Evans, 1989), (Karsai & Wenzel, 1998) and (Singh, Shah, & Kobti, 2013). In this paper, we have analyzed the effect of positive social influence on the emergence of DOL and through simulations have shown that this is also an important factor to improve specialization. Thus we conclude that increase in social influence rate leads to increase in the level of specialization.

The other finding in this paper is cooperative behavior between different organizations in the cluster. It is a general idea that one person or one organization is not capable enough to acquire specialization in several tasks so they need support from others. Our formulation and simulations demonstrate that when any organization is suffering from task workload then the cooperative behavior from neighbors helps them to survive. It also gives chance to those neighbors who are sitting idle and doing nothing. We conclude that the emergence of cooperative behavior increases the specialization in the cluster.

In the future work there are so many points which we want to be improved upon. Though, we have taken the weights α_j measuring the strength of the positive social influence for the task j to be fixed for each task j, α_j may be taken as an appropriately chosen function of j in future work as the influence rates may be different for each individual organization for different tasks in the cluster. Social network is also a key point to be taken in future work because we want to test on different networks and compare the results. Besides these points another important point which we wish to have a detailed discussion in future is complex modeling of industry cluster.

CHAPTER 5

Conclusions and Future Work

In this thesis, we have developed a new model for industrial clusters and also improved previously build WASPS model. A new hybrid model is proposed by introducing a new formula for genetic pull in Chapter 3, thereby achieving a higher level of DOL and QOW as compared with the WASPS model. The novelty of our approach is that we analyze the DOL and QOW by introducing the concept of continuous and random demand in our model. The demand changes depending on several factors like colony size, climatic changes across social systems as well as other biological systems. Hence, we proposed a model where demand is oscillatory in nature and stabilizes eventually. Keeping these requirements in mind, we constructed a formula for the demand, which is both oscillatory and eventually stabilizes around a point. Numerical experiments were performed through simulations for discrete, random and continuous demands. The level of DOL and QOW are higher for continuously varying demand than the randomly chosen demand with lower values when the demand is restricted to discrete values. The continuous choice of demand has the advantage that in each time step, the stimulus changes thus depicting the real world more accurately. Thus, we conclude that continuous choice of demand is better followed by the random and then discrete demand to achieve higher level of specialization and better quality of work.

We have developed a general model of specialization which can be applied to various fields. Due to the current hot ongoing research on the industry cluster, we shifted our attention towards this area and developed a new model. In this model, we put emphasis on positive social influence and construct a formula for task selection influenced by the positive social response from the neighboring organizations and our finding is that positive social influence increases specialization along with group size and task number. It is quite a significant finding because earlier papers showed the emergence of specialization with increment in group size and task number. The second important finding in this model is the emergence of cooperative behavior amongst organization in the cluster due to the positive social response which also increases the overall specialization in the cluster. We have constructed a new mathematical formulation for task workload and have shown that in critical situations when individual organization is suffering from task workload and need help then emergence of cooperative behavior among neighboring organizations come into play. Till date, we did not find any work on adaptation of cooperative behavior through positive social response in the specialization model for the industry cluster. We may conclude that positive social influence and adaptation of cooperative behavior in industry clusters are the two driving factors to increase specialization.

In the future work, we would like to implement more than one cluster which is interacting with each other regarding common goal.

We will be interested to make more complex system of industry cluster in which individual organizations are competing for different goals rather than a single goal. It is very interesting and useful idea to expand because it give a better overall picture of industry cluster and can be applied to any real world business problem.

We would also like to test our model on different types of networks to study the emergence of specialization.

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VITA AUCTORIS

NAME:	Saurabh Singh
PLACE OF BIRTH:	Varanasi , India
YEAR OF BIRTH:	1986
EDUCATION:	Btech (Computer Science), UPTU India, 2009.