UNIVERSITY OF SOUTHAMPTON

Faculty of Physical Engineering and Science
School of Electronics and Computer Science

A project report submitted for the award of
MEng Computer Science

Supervisor: Dr Tim Norman

Reinforcement Learning agents for Online Elastic Resource allocation in Mobile Edge Computing

by **Mark Towers**

May 2, 2020

University of Southampton

Abstract

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Edge clouds enable computational tasks to be completed at the edge of the network, without relying on access to remote data centres. A key challenge in these settings is that servers have limited computational resources that often need to be allocated to many self-interested users. Existing resource allocation approaches usually assume that tasks have inelastic resource requirements (i.e., a fixed amount of compute time, bandwidth and storage), which may result in inefficient resource use. In this paper, we expand previous work, that utilises an elastic resource requirement mechanism, to an online setting such that job will arrive over time with the task prices and resource allocation determined through agents trained using reinforcement learning.

Contents

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I declare that this thesis and the work presented in it is my own and has been generated by me as the result of my own original research.

I confirm that:

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Signed:..... Date:.....

Acknowledgements

I want to thank my parents for all of the support they have given me because I would not be where I am now without them. Also to my housemates for surviving with me pestering them about proof reading badly written papers and for dealing with me stressing about this project.

This project wouldn't have started without Dr Sebastian Stein, Professor Tim Norman and a team of Pennsylvania State University that has produced a paper investigating the static case of this problem. Thank to all of them for sharing ideas and support for that paper and this project.

Also to Professor Tim Norman for this constant guidance over the project and the wisdom to know what for me to investigate and implement.

Chapter 1

Introduction

Cloud computing is a rapidly growing technology with competition from Google, Amazon, Microsoft and others that aims to allow users to run computer programs that are too large, difficult or time consuming for users to run locally. These services provide the computational resources, e.g. CPU cores, RAM, hard drive space, bandwidth, etc to be able to run such programs. However, as these resources are limited, bottlenecks can occur when numerous users require large amounts of these resources, limiting the number of tasks [1] that can be run on servers simultaneously.

For Google Cloud Services (GCP), Microsoft Azure or Amazon Web Services, their cloud computing facilities contain huge server nodes limiting the probability that such a bottleneck occurs. But if such an event does occur, users have a range of data centres across the global to use if a single data centre does becomes overloaded with requests. Therefore this work considers a developing paradigm (Mao et al., 2017) called mobile edge computing (Hu et al., 2015) referred to as MEC in this work. MEC aims to provide users the ability to run their tasks closer to them reducing latency, network congestion and providing better application performance.

Currently disaster response (Guerdan et al., 2017), smart cities (Alazawi et al., 2014) and the internet-of-things (Corcoran and Datta , 2016) are all areas that utilise MEC due to its ability to process computationally small tasks locally with low latency. For example, in smart cities, this allows for smart intersection systems using road-side sensors or smart traffic lights, that are based on cameras

[1] Tasks, Programs and Jobs will be used interchangeable to refer to the same idea of a computer programs that has a fixed amount of resources required to compute.

works to minimise cars waiting times at traffic lights (Mustapha et al., 2018). Or for the police to analyse CCTV footage to spot suspicious behaviour or to track people between cameras (Sreenu and Saleem Durai, 2019). In the case of disaster response, maps can be produced using data from autonomous vehicles' sensors that can then be used in the search for potential victims and support responders in planning rescues (Alazawi et al., 2014).

However the problem of bottlenecks is of particular relevant to mobile edge computing. As instead of large server farms that can be geographically distant from the users, servers are significantly smaller, possibly just high powered desktop computers or single server nodes. This results in greater demand on individual server resources, meaning that efficient allocation of these resources is of growing importance as the technology continues to grow.

However it is believed that there are shortcomings in existing research about resource allocation within MEC (Farhadi et al., 2019; Bi et al., 2019) due to the nature of how task resource usage is determined. Traditionally, a user would submit a request for a fixed amount of resources, i.e. 2 CPU cores, 8GB of RAM, 20GB of storage, that would be allocated for the user. As a result, these resources can't be redistributed until the user finishes with them. The reason that this form of resource allocation is used and effective within cloud computing is due to its simplicity for the user to decide resource requirements, utilisation of simple linear pricing mechanisms and it is rare for servers with large resource capacity to have bottlenecks. However it is believed that the problem of bottlenecks within MEC systems, warrant the investigation of an alternative resource allocation mechanism.

In previous work a novel resource allocation mechanism (by this author (Towers et al., 2020)) was proposed to allow for significantly more flexibility in determining resource usage with the aims of reducing possible bottlenecks. The mechanism is based on the principle that the time taken for an operation to complete is generally proportional to the resources provided for the operation. An example for this is downloading an image, the time taken is proportional to the bandwidth allocated. This sort of flexibility is similarly true for computing most tasks [2] or sending results back to the user. Based on this principle, a modified resource allocation mechanism can be reconstructed such that the users provide the task's total resource usage over its lifetime instead of the requested resource usage.

[2] It is well known that some algorithm are not scalable making this principle incompatible with those tasks. Therefore in this work consider the case for algorithms that can be scalable linearly and leaves case of non-scalable tasks to future work.

As a result, a task's resource usage is determined by the server rather than the user increasing a server's flexibility. Using this flexible resource allocation mechanism, algorithms proposed achieved 20% better than fixed resource allocation mechanisms in one-shot cases investigated by Towers et al. (2020). This is due to the ability to properly balance resources, preventing bottlenecks occurring as often, which in turn allowed more tasks to run simultaneously and to reduce the price for users.

Moreover this work only considered the proposed mechanism within a static or one-shot case where all tasks were presented at the first time step, where tasks would be auctioned and resource allocated. As a result, practically the proposed algorithms would require tasks to be processed in batches such that servers would bid on all tasks submitted every 5 minutes for example. This also means that while resources could dynamically allocated at the first time step, they would not be changed during the next batches until the task was completed. This work aims to address this problem.

This was achieved by introducing time into the optimisation problem (outlined in section 3.1). As a result, task can now arrive over time and for servers to redistribute resources at each time step. However, all previous mechanisms proposed in Towers et al. (2020) are incompatible with this modified flexible optimisation problem. Therefore this work investigates reinforcement learning methods that train agents to optimally bid on tasks based on their resource requirements and efficiently allocate resources to tasks running on a server.

This report is set out in the following chapters. Chapter 2 investigates previous research that this project builds upon within both resource allocation in cloud computing and reinforcement learning. Chapter 3 proposes a solution to the problem outline in Chapter 1. The proposed solution is then implemented in chapter 4 with testing and evaluation in Chapter 5 respectively. Chapter 6 presents the conclusion along with possible future work on the project.

In addition to this report, the paper referred to as Towers et al. (2020) was completed within this academic year and thus considered part of this project's work. A copy of the paper can be found in Appendix A. In addition to this paper, the work was also presented at SPIE Defense and Commercial Sensing 2020 as a recorded digital presentation. A copy of the slides can be found in Appendix B with a link to the recording.

Chapter 2

Literature Review

There is a considerable amount of research in the area of resource allocation and task pricing in cloud computing, in case auction mechanisms are used to deal with competition (Kumar et al., 2017; Bi et al., 2019). Section 2.1 presents the different approaches to resource allocation and pricing mechanisms in cloud computing.

The proposed solution of the project (presented in chapter 3) uses a form of machine learning, called Reinforcement Learning. Section 2.2 covers the current state-of-the-art algorithms in Q learning and policy gradient research.

2.1 Resource allocation and pricing in Cloud Computing

A majority of approaches taken for task pricing and resource allocation in cloud computing uses a fixed resource allocation mechanism, such that each user requests a fixed amount of resources from a server for a task. However this mechanism, as previously explained, provides no control for the server over the quantity of resource allocated to a task, only determining the task price. As a result, a majority of approaches don't consider the server management of resource allocation. Thus research has focused on designing efficient and strategyproof auction mechanisms.

Work by Kumar et al. (2017) provides a systematic study of double auction mechanisms that are suitable for a range of distributed systems like Grid computing, Cloud computing, Inter-Cloud systems. The work reviewed 21 different proposed auction mechanisms over a range of important properties like Economic Efficiency,

Incentive Compatibility and Budget-Balance. In a majority of the proposed auction mechanisms, truthfulness was only considered for the user, thus a truthful multi-unit double auction mechanism was presented as novel double-sided truthful auction meaning both users and server should act truthfully.

Deep reinforcement learning was implemented by Bingqian Du (2019) to learn resource allocation and pricing in order to maximise cloud profits. Deep neural network models with long/short term memory units enabled state-of-the-art online cloud resource allocation and task pricing algorithms that had significantly better results than traditionally online mechanisms in terms of profit made and number of users accepted. The system considered both the pricing and placement of virtual machines in the system to maximise the profits of cloud providers through the use of deep deterministic policy gradient (Silver et al., 2014) to train agents. Users would request a type of virtual machine from the system that a server would allocate to a user where the price and placement of the virtual machine within possible servers by a neural network agent. The deep reinforcement learning models were trained using real-world cloud workloads and achieved significantly high profit even in worst-case scenarios.

Some approaches have been taken to increase flexibility within fog cloud computing by Bi et al. (2019) enabled efficient distribution of data centers and connections to maximise social welfare. A truthful online mechanism was proposed that was incentive compatible and individually rational to allow tasks to arrive over time by solving a integer programming optimisation problem. Similar research in Farhadi et al. (2019), considers the placement of code/data needed to run specific tasks over time as demand changes while considering operational costs and system stability. An approximation algorithm achieved 90% of the optimal social welfare by converting the problem to a set function optimisation problem.

Previous work by this author in Towers et al. (2020) proposed the novel resource allocation mechanism and optimisation problem that this project works to expand. The paper presents three mechanisms for the optimisation problem, one to maximise the social welfare and two auction mechanisms for self-interested users. The Greedy algorithm presented allows for quick approximation of a solution through the use of several heuristics in order to maximise the social welfare. Results found that the algorithm achieved over 90% of the optimal solution given certain heuristics compared to a fixed resource allocation solution that achieved 70%. The algorithm has polynomial time complexity with a lower bound of $\frac{1}{n}$ however in practice achieves significantly better results.

The work also presented a novel decentralised iterative auction mechanism inspired by the VCG mechanism (Vickrey, 1961; Clarke, 1971; Groves, 1973) in order to iteratively increase a task's price. As a result, a task doesn't reveal its private task value. This may be particularly interesting with military tactical network such that countries do not need to reveal the important of a task to another coalition country. The auction mechanism achieves over 90% of the optimal solution due to iteratively solving a specialised server optimisation problem. The third algorithm is an implementation of a single parameter auction (Nisan et al., 2007) using the greedy algorithm to find the critical value for each task. Using the greedy algorithm with a monotonic value density function means the auction is incentive compatible and inherits the social welfare performance and polynomial time complexity of the greedy mechanism.

2.2 Reinforcement Learning

Computer scientists have always been interested in comparing computers against humans (Turing, 1950). A key characteristic of humans is the ability to learn from experience, while computers must have this programed in to solve programs. Researchers have invented a variety of ways for computers to learn from experience, that are broadly grouped into three categories: supervised, unsupervised and reinforcement learning. Supervised learning uses inputs that are mapped to known outputs, an example is image classifications. Unsupervised learning in comparison doesn't have a known output for a set of inputs, instead algorithms try to find links between similar data, for example data clustering.

However both of these techniques are not applicable for cases where agents must interact with an environment making a series of actions that result in rewards over time. Algorithms designed for these problems fall into the category of Reinforcement Learning. Algorithms utilise environments that can be generally formulated as a Markov Decision Process (Bellman, 1957) where agents select actions based on the environment state that results in a new state and resulting reward as shown in figure 2.1.

Q-learning algorithm Watkins and Dayan (1992) is a learning method used for estimating the action-value function, called the Q value, which is the basis for modern reinforcement learning algorithms. The Q value represents the estimated discounted reward in the future given an action in a particular state.

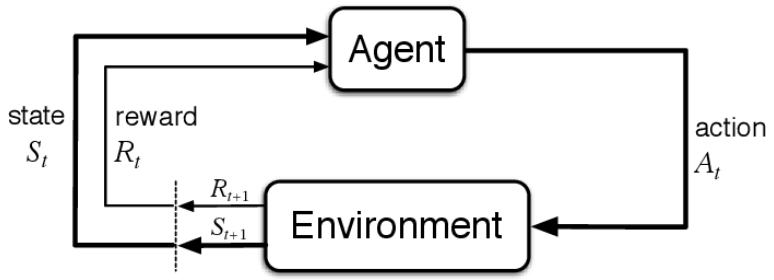

FIGURE 2.1: Reinforcement learning model (Source: Sutton and Barto (2018))

Equation (2.1) gives a mathematically description where rewards in the future are discounted. A recursive version of this equation can be formulated as equation (2.2) where the next state is the max Q value of the next state-action.

$$Q(s_t, a_t) = E[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+2} + \cdots] \tag{2.1}$$

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \cdot (r_t + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t)) \tag{2.2}$$

However the curse of dimensionally was found to be a major problem for using Q learning. As it requires a table for every state-actions pairs so that as the number of state dimensions or actions increased, the table will grow exponentially. This made the method impractical for problems with large state space due to both the table size and the required training time.

Therefore function approximators are used to circumvent this problem, typically done using neural networks due to their ability to approximate any function (Csáji, 2001) and to be trained using gradient descent. Work by Mnih et al. (2013), that implemented a deep convolution neural network achieved state-of-the-art performance in six of seven games tested as part of the Atari game engine, with three of these scores being superhuman. This was done through using of two different neural network, a model and target network in which the target network was slowly updated by the model network to act as a slowly updating target Q value. An experience replay buffer was also implemented to enable the agent to learn from previous actions. Follow up work by Mnih et al. (2015) found that with no modifications to the hyperparameters, neural network or training method; state-of-the-art results were achieved in almost all 49 Atari games with superhuman results in 29 of these games. The work showed that deep neural networks could be trained through observing just the raw game

pixels and knowledge of the game score over time to achieve scores better than humanly possibly.

Due to this research, a large number of heuristics have been proposed to the loss function (van Hasselt et al., 2015), network architecture (Wang et al., 2015), experience replay buffer (Schaul et al., 2015) and more to improve the optimality of the agent. A combined agent (Hessel et al., 2017) applying a range of heuristics enabling it to achieved over 200% of the original DQN algorithm in score.

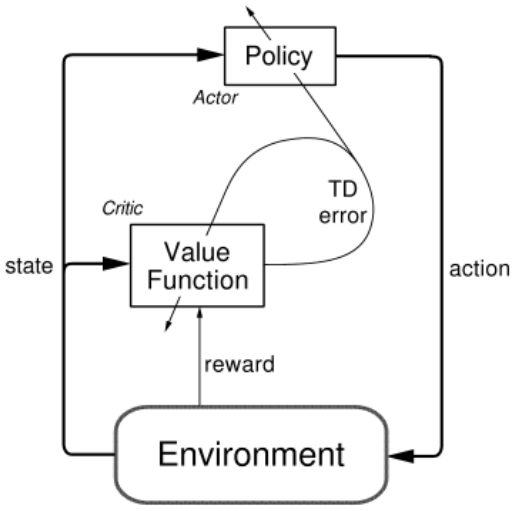

FIGURE 2.2: Actor Critic model (Source: Sutton and Barto (2018))

Using the base of Q-learning, policy gradient agents, shown in figure 2.2 separate the action selection policy from the Q-value function known as the critic. In deep Q networks, actions are selected on the maximum Q-value for all of the actions, however this requires actions to be discretized. By splitting the actions from the Q values, an actor chooses an action based on the environment state allowing for both discrete and continuous action space. With the actor being trained by the value of the critic agent that uses both the state and actor actions to calculate the Q value for the agent. This has the additional advantage that agents don't require epsilon greedy action selection during training which can result in the DQN policy differing from the optimal policy. As a result policy gradient has been used to master the game of Go (Silver et al., 2017) and achieve top 1% in both Dota 2 (OpenAI, 2018) and Starcraft 2 (Vinyals et al., 2017) video games.

Chapter 3

Optimising resource allocation in MEC

In chapter 1, the problem that this project aims to address was outlined along with a short description of the proposed solution. This chapter builds upon that, giving a formal mathematical model for the problem in section 3.1. Section 3.2 proposes an auction mechanism in order to pay servers for their resources in order to deal with self-interested users and as server are payed for use of their services.
Using the optimisation problem and auction mechanism from the previous sections, agents for both auction and resource allocation are proposed, in section 3.3, that learns together to maximise a server's profits over time.

3.1 Resource allocation optimisation problem

Using the flexible resource principle, the time taken for a operation to occur, e.g. loading of a program, computing the program and sending of results, etc, is proportional to the amount of resources allocated to complete the operation. A modified version of a resource allocation optimisation model can be formatted by building upon a similar formulation in Towers et al. (2020).

A sketch of the whole system is shown in figure 3.1. The system is assumed to contain a set of $I = \{1, 2, \ldots, |I|\}$ servers that are heterogeneous in all characteristics. Each server has a fixed resource capacity: storage for the code/data needed to run a task (e.g., measured in GB), computation capacity in terms of CPU cycles

per time interval (e.g., measured in GHz), and communication bandwidth to receive the data and to send back the results of the task after execution (e.g., measured in Mbit/s). The resources for server i are denoted: S_i for storage capacity, W_i for computation capacity, and R_i for communication capacity. The system occurs over time that is defined as the set $T = \{1, 2, \ldots, |T|\}$.

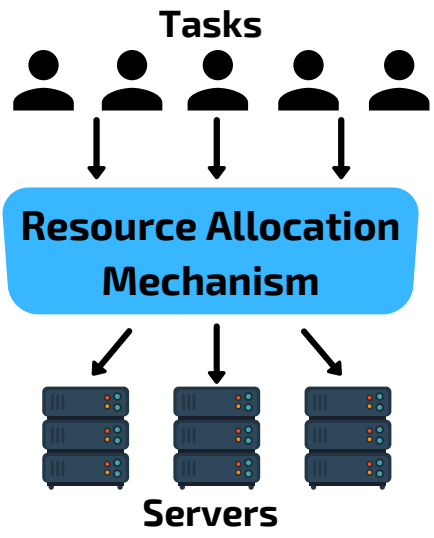

FIGURE 3.1: System model

The system is also assumed to contain a set of $J = \{1, 2, \ldots, |J|\}$ heterogeneous tasks that require services from one of the servers in set I. To run any of these tasks on a server requires storing the appropriate code/data on the same server. This could be, for example, a set of images, videos or Convolutional neural network layers used in identification tasks.

The storage size of task j is denoted as s_j with the rate at which the program is transferred to a server at time t being $s'_{j,t}$. For a task to be computed successfully, it must fetch and execute instructions on a CPU. We consider the total number of CPU cycles required for the program to be w_j, where the number of CPU cycles assigned to the task at time t is $w'_{j,t}$. Finally, after the task is run and the results obtained, the latter needs to be sent back to the user. The size of the results for task j is denoted with r_j, and the rate at which they are sent back to the user is $r'_{j,t}$ on a server at time t.

The allocation of a task to server is denoted by $x_{i,j}$ for each task $j \in J$ and each server $i \in I$. This is constrained by equation (3.1) meaning that a task can only be allocated to a single server at any point in time.

$$\sum_{i \in I} x_{i,j} \leq 1 \qquad \forall j \in J \tag{3.1}$$

$$x_{i,j} \in \{0, 1\} \qquad \forall i \in I, j \in J \tag{3.2}$$

As the task must complete each stage in series, additional variables are required to track the progress of each task stage. $\hat{s}_{j,t}$ denotes the loading progress of the

task, $\hat{w}_{j,t}$ denotes the compute progress and $\hat{r}_{j,t}$ denotes the sending progress of the task. Each of these variables are updated recursively depending on the progress in the previous time step plus the resources allocated. Progress is also limited to each of the tasks total required resources in constraints (3.6), (3.7) and (3.8).

$$\hat{s}_{j,t+1} = \hat{s}_{j,t} + \hat{s}'_{j,t} \qquad \forall j \in J, t \in T \tag{3.3}$$

$$\hat{w}_{j,t+1} = \hat{w}_{j,t} + \hat{w}'_{j,t} \qquad \forall j \in J, t \in T \tag{3.4}$$

$$\hat{r}_{j,t+1} = \hat{r}_{j,t} + \hat{r}'_{j,t} \qquad \forall j \in J, t \in T \tag{3.5}$$

$$\hat{s}_{j,t} \leq s_j \qquad \forall j \in J, t \in T \tag{3.6}$$

$$\hat{w}_{j,t} \leq w_j \qquad \forall j \in J, t \in T \tag{3.7}$$

$$\hat{r}_{j,t} \leq r_j \qquad \forall j \in J, t \in T \tag{3.8}$$

Every task has an auction time, denoted by a_j and a deadline, denoted by d_j. This is the time step when the task is auctioned and the last time for which the task can be completed successfully. During this time, the time required to send the data/code to the server, run it on the server, and get back the results to the user which must occur in order. As a server couldn't start computing a task that was already fully loaded on the machine, for example. A deadline constraint can simply be constructed such that the sending results progress is finished on the deadline time step (equation (3.9)).

$$\hat{r}_{j,d_j} = r_j \qquad \forall j \in J \tag{3.9}$$

As servers have limited capacity, the total resource usage for all tasks running on a server must be capped. The storage constraint (equation (3.10)) is unique as the sum of the loading progress for each task allocated to the server. While the computation capacity (equation (3.11)) is the sum of compute resources used by all of the tasks on a server i at time t and the bandwidth capacity (equation (3.12)) being less than the sum of resources used to load and send results back by all allocated tasks.

$$\sum_{j \in J} \hat{s}_{j,t} x_{i,j} \leq S_i, \qquad \forall i \in I, t \in T \tag{3.10}$$

$$\sum_{j \in J} w'_{j,t} x_{i,j} \leq W_i, \qquad \forall i \in I, t \in T \tag{3.11}$$

$$\sum_{j \in J} (s'_{j,t} + r'_{j,t}) x_{i,j} \leq R_i, \qquad \forall i \in I, t \in T \tag{3.12}$$

3.2 Auctioning of Tasks

While the mathematically description of the problem presented in the previous section doesn't consider any auctions occurring. In real life servers normally wish to be paid for the use of their resources. However due to the modifications that this project has to make to the optimisation problems, all of the auction mechanisms discussed in section 2.1 cannot be used. This is true as the user is not requesting a fixed amount of resources nor can the available resources be easily computed as this is dynamic, depending on the different stages of tasks allocated to a server. The modification also affects the algorithms presented in Towers et al. (2020) as they assume that all of the task stages can occur concurrently. This means that a novel or modified auction mechanism must be used to deal with these changes. Due to the complexities of devising a new auction mechanism and the large corpus of research on auctions already, outline of the most common auctions is presented in table 3.1 with their respective properties in table 3.2.

Auction type	**Description**
English auction	A traditional auction where all participant can bid on a single item with the price slowly ascending till only a single participant is left who pays the final bid price. Due to the number of rounds, this requires a large amount of communication.

Dutch auction	The reverse of the English auction, where the starting price is higher than anyone is willing to pay with the price slowly dropping till the first participant "jumps in". This can result in sub-optimal pricing if the starting price is not highest enough or a large number of rounds is required till anyone bids. Plus due the auctions occurring over the internet, latency can have a large effect on the winner.
Japanese auction	Similar to the English auction except that the auction occurs over a set period of time with the bid increasing over time and last highest bid being the winner. This means that it has the same disadvantages as the English auction except that there is no guarantee that the price will converge to the maximum. Plus additional factors like latency can have a large effect on the winner and resulting price. But due to the time limit, it has a known amount of time till it finishes unlike the English or Dutch auctions.
Blind auction	Also known as a First-price sealed-bid auction, all participants submit a single secret bid for an item with the highest bid winning. As a result there is no dominant strategy (not incentive compatible) as an agent would wish to bid only a small amount more than the next highest price in order overpay for the item. But due to there being only a single round of biding, latency doesn't affect an agent and allows many more auctions could occur within the same time compared to the English, Dutch or Japanese auctions.
Vickrey auction (Vickrey, 1961)	Also known as a second-price sealed bid auction, participants each submit a single secret bid for an item with the highest bid winning like the blind auction. However the winner only pays the price of the second highest bid. Because of this, it is a dominant strategy (incentive compatible) for an agent to bid its true value as even if the bid is much higher than all other participants its doesn't matter as they pay the minimum required for them to win.

TABLE 3.1: Descriptions of feasible auctions for the project: English, Dutch, Japanese, Blind and Vickrey auction

The auction properties that this project considers most important is the auction

Auction	Incentive compatible	Number of rounds	Fixed time length
English	False	Multiple	False
Japanese	False	Multiple	True
Dutch	False	Multiple	False
Blind	False	Single	True
Vickrey	True	Single	True

TABLE 3.2: Properties of the auctions described in Table 3.1

time length and incentive compatibility. This is as, online auction wish to be fast that is incompatible with the English, Dutch and Japanese auctions and incentive compatible means that an optimal strategy actually exists to player to play towards. Because of these two properties, the Vickrey auction (Vickrey, 1961) has been chosen. An additional advantage of using the Vickrey auction, with reinforcement learning agent, is that as it is incentive compatible, agents dont need to learn how to outbid another agent. They only needs learn to effectively evaluate each task instead of through demand meaning that allowing agents to possibly learn through self-play.

However a modification must be made due to servers generate the prices for tasks rather than task suggesting a price to servers. Because of this, the auction is reversed, such that the bid with the minimum price wins the task instead of the maximum price. The auction therefore works by allowing all servers to submit their bids for a task with the winner being the server with the lowest price, with the task actually paying second lowest price.

3.3 Auction and resource allocation agents

Using the optimisation formulation and auction mechanism from the previous two sections, the problem can be modelled as Markov Decision Process (Bellman, 1957) which allows the environment to be model as figure 3.2. This separates out the auction and resource allocation part of the problem with separate agents into almost similar environments to act during their respective part of the problem. Subsection 3.3.1 and 3.3.2 proposes agents for the auction environment and resource allocation environment respectively.

The environment is believed to possibly be of interest for multi-agent reinforcement learning researchers as the aim of the environment is cooperative (to maximise the social welfare) but knowing that servers can act self-interestedly during the

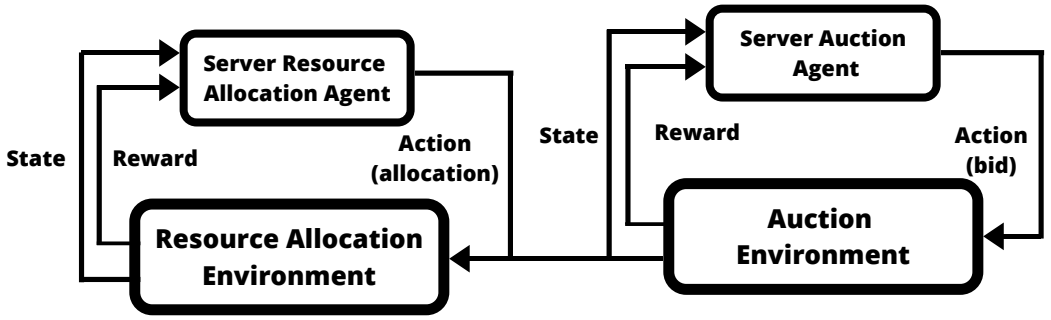

FIGURE 3.2: Markov Decision process system model

auctions in order to maximise their private profits. But the resource allocation agent must work cooperatively in allocating of resources for each task as the server wishes to complete as many tasks as they can. This author believes that this type of environment is unique within reinforcement learning.

3.3.1 Proposed auction agents

Traditionally pricing mechanisms (Al-Roomi et al., 2013) rely on mixture of metrics: resource availability, resource demand, quality of service, task resource requirements, task resource allocation quantity, etc to determine a price. However these values are difficult to approximate during the auction with this program case. So due to the complexity of deriving this function, reinforcement learning will be used with the aim to learn an optimal policy to maximise the profits of the server over time. Simple heuristics will also be implemented in order compare the effectiveness of the reinforcement learning to untrained heuristics.

Neural Network	Description
Artificial neural networks (McCulloch and Pitts, 1943)	Originally developed as a theoretically approximation for the brain, it was found that for networks with at least one hidden layer, neural networks could approximate any function (Csáji, 2001). This made neural networks extremely helpful for cases where it would normally be too difficult for a human to specify the exact function as they can be trained through gradient descent and supervised learning to find a close approximation to the true function.

Recurrent neural network (Elman, 1990)	A major weakness of artificial neural networks is that it must use a fixed number of inputs and outputs making it unusable with text, sound or video where previous data is important for understanding the inputs. Recurrent neural network's extend neural networks to allow for connections to previous neurons to "pass on" information. However recurrent neural networks struggle from vanishing or exploding gradient during training.
Long/Short Term Memory (Hochreiter and Schmidhuber, 1997)	While recurrent neural network's can "remember" previous inputs to the network, it also struggles from the vanishing or exploding gradient problem where gradient tends to zero or infinity making it unusable. LSTM aim to prevent this by using forget gates that determines how much information the next state will get, allowing for more complexity information to be learnt compared to recurrent neural networks.
Gated Recurrent unit (Chung et al., 2014)	Gated recurrent unit are very similar to long/short term memory, except for the use of a different wiring mechanisms and the one less gate, an update date instead of two forgot gates. These changes mean that gated recurrent units run faster and are easier to code than long/short term memory, however are not as expressive meaning that less complex functions can be encoded.
Neural Turing Machine (Graves et al., 2014)	Inspired by computers, neural turing machines build on long/short term memory by using an external memory module instead of memory being inbuilt to the network. This allows for external observers to understand what is going on much better than other networks due to their black-box nature.
Differentiable neural computer (Graves et al., 2016)	An expansion to the neural turing machine that allows the memory module to scalable in size allowing for additional memory to be added if needed.

TABLE 3.3: Neural network layer descriptions

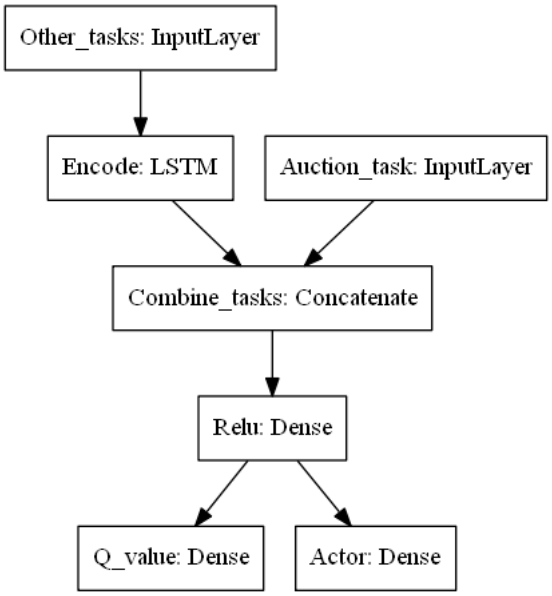

FIGURE 3.3: Task pricing network architecture

As the action space of the agent is continuous, a deep deterministic policy gradient (Silver et al., 2014) agent will be implemented. The action shape can also be discretized allow deep Q learning agents Mnih et al. (2013) to be trained as well. In order to compare alternative learning methods and the affect of discretizing the action space on results, agents will use neural networks as it is known to be able to approximate any function (Csáji, 2001). Because of this, a long/short term memory (Hochreiter and Schmidhuber, 1997) layer will be used as it allows for multiple inputs, and outputs are single vector that will have several additional layers to allow additional complexity. The network will end at a single ReLU neuron for DDPG or multiple logit activation neurons for DQN agents as shown in Figure 3.3.

3.3.2 Proposed resource allocation agents

When a new task is allocated to the server or a task completes a stage, server resource need to be redistributed to the task. As the problem of how to allocation resources isn't as complex as the agent pricing in section 3.3.1, both simple heuristics and reinforcement learning agents will be implemented in order to compare effectiveness.

However a similar problem exists as with the proposed auction agents (in subsection 3.3.1). Due to knowing how to allocate resources to a single task requires being aware of the resource requirements of other tasks and how they are being weighted

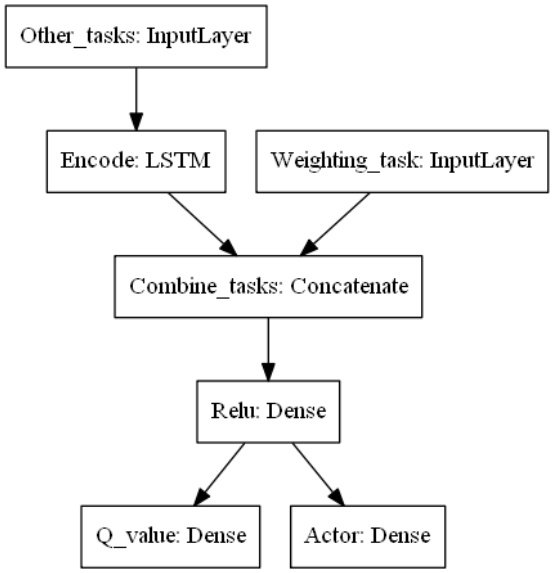

FIGURE 3.4: Resource weighting network architecture

on the server. Therefore a similar network is proposed to allow for the other tasks to be passed into the network at the same time it is weighting a task. This is shown in figure 3.4

A weighting heuristic is proposed for the network output as well, such that the network doesn't output the raw resources allocated for a task but rather a weighted value for the resources needing to allocated for the task. This has the advantage of being a simpler function to approximate for agents but with a similar expressiveness as an exact resource usage function. This also avoids the problem of the network either over allocating the resources to tasks or severely under allocating resources.

Chapter 4

Implementing a flexible resource allocation environment and agents

In order to implement a solution from chapter 3, an MEC network environment must be simulated due to the impractically of setting up such a network and in order to train the agents offline as proposed in section 3.3. This chapter splits the implementation into three sections: the environment simulation (section 4.1), server auction and resource allocation agents (section 4.2) and training of agents (section 4.3).

The implementation discussed below as written in Python and available to download from Github [1]. The reason for the use of python is number of modules available for reinforcement learning and the speed of development.

4.1 Simulating edge cloud computing services

While the aim of the environment is the simulate accurately MEC servers, the implementation of the environment must allow agents to train on interact and training on the environment efficiently. Therefore it has been implemented as an OpenAI gym (Brockman et al., 2016), the de facto standard for implementing reinforcement learning environment for researchers. However the standard specification must be modified due to the problem being multi-agent and multi-step.

An example for running the environment is in listing 4.1. There are three sections to the code: the first is the construct an environment using the constructor,

[1] https://github.com/stringtheorys/Online-Flexible-Resource-Allocation

where the environment settings are passed that determines the number of servers, tasks and their attributes. These attributes are determined using uniform random numbers between a maximum and minimum values that are synthetically generated for each variable. The second step is to create the environment using the reset function returning the new environment state. The environment state contains a task if one needs to be auctioned and a dictionary of server to their current task state. Using these states, each server can generate actions either using the auction agent or resource allocation agent depending if a task needs auctioning. The final part is to take a step using the server actions that returns an updated server state, the rewards for the actions, if the environment is finished and an extra information from the steps taken. The rewards is a dictionary of each of servers with either the winning price for the auctioned task or a list of tasks that have finished either because they ran out of time or completed the task early, depending on the step taken.

```
# Load the environment with a setting
env = OnlineFlexibleResourceAllocationEnv('settings.env')

# Generate the environment state
server_state = env.reset()

for _ in range(1000):
    # Generate actions
    if server_state.auction_task:
        actions = {
            server: auction_agent.bid(state)
            for server, state in server_state
        }
    else:
        actions = {
            server: resource_allocation_agent.weights(state)
            for server, state in server_state
        }

    # Take environment step
    server_state, reward, done, info = env.step(actions)

    # If the environment is finished then reset it
    if done:
        server_state = env.reset()
```

LISTING 4.1: Example code for running the environment

4.1.1 Weighted server resource allocation

A particular complication of the environment is to distribute server resources due to the fact that the resource allocation agents provide a resource weighting

rather than the actually task resource usage. Because of this, a novel algorithm was implemented to convert the weighting to actual resources for each task.

To allocate the computational resources is relatively simple compared to allocating resources for both storage and bandwidth. For computational resources, the algorithm checks first if the weighted resources is greater than the quantity required for the task to finish the compute stage of a task. If this is true then a resources needed for the task to complete the compute stage are allocated. However, this also means that the weight resources available for each task is increased due to a task not using all of the resources it could. This type of checking is repeated till no task can be finished with its weighted resource within this time step. For the remaining task, they are just allocated their weighted compute resources.

For allocating storage and bandwidth, this is more difficult is due to the fact that when the server is still loading the task, the server is allocating both storage and bandwidth resources while also allocating bandwidth resources to tasks sending results back to users. Because of this, a tension exists between allocating bandwidth and storage resources for all of the tasks fairly. Algorithm was therefore chosen to gives priority when allocating resources to the tasks sending results as these tasks are more likely to be finished and aims to not penalise the server for not completing the task within the deadline.

To allocate resources, a similar function to used to the one for allocating compute resources. First a check if done using the weighted bandwidth resources to see if any task sending results will be finished with the resources. This process is also repeated for the tasks loaded onto a server with the additional check that there is enough available storage for the new data to be added. For any remaining task, this process is repeated till all of the available resources are allocated in the time step. As a results, using this algorithm, the converting between weightings to resources allowing for allocating of almost all of the server's resources with no resources unused.

4.2 Implementing Auction and resource allocation agents

To implement auction and resource allocation agents, generic abstract classes for both were implemented with a bid function for the auction agent and a

weighting function for the resource weighting agent. The bid had arguments for the task being auctioned, the server with its currently allocated tasks and current time step. These attribute were used by the reinforcement learning policies explained in subsection 4.2.1 to calculate the auction bid price. For the weighting function in the resource weighting agent, the function took a server and a list of the server's currently allocated tasks along with the current time step. Using these attributes, agents can return a dictionary of task weighting.

A range of different reinforcement learning techniques have been implemented, outlined in Table 4.1, in order to explore the different options that a server would have available to learn its policies.

4.2.1 Implementing reinforcement learning policies

The policies outlined in table 4.1 were implemented using tensorflow (Abadi et al., 2015), a python module developed by Google that provides programmers the ability to construct neural network, backpropagation with custom loss function and more. For each of the algorithms, an abstract class was implemented with a function for training and saving of the agent neural networks. For each of these algorithms, a task pricing and resource weighting class was implemented that are subclasses for the abstract algorithm class.

Both deep Q networks and policy gradient algorithm are based on the Q function (explained in section 2.2)) which tries to approximate the reward at the next time step. To do this requires a reward function and a next observation to compare to in order to train these agents. The agent's reward function and agent training observations are detailed in subsection 4.2.2 and 4.2.3.

A particular problem that this project encounter was with using recurrent neural network as inputs. This is as the number of inputs is not fixed meaning that during training, using a minibatch was not possible as most of the inputs all had different input lengths and tensorflow requires all inputs to have a known, fixed length. Originally this was sidestepped by calculating the loss for each input individually then finding the mean loss and gradient to update the networks with. However this was found to be computationally impractical making the method impossible to run agents to long enough. Because of this, a solution was found by padding all of the inputs to have the same size using the tensorflow preprocessing module with the sequence.pad_sequence function. As a result, training became 10x faster making large scale testing practical.

Policy Type	Explanation
Dqn (Mnih et al., 2015)	A standard deep Q learning agent that discretizes the action space with a target neural network and experience replay buffer.
Double Dueling DQN (van Hasselt et al., 2015; Wang et al., 2015)	A combination of two heuristics for the standard deep Q learning agents that uses a modified td target function and a modified networks that separates state value and action advantage which can recombined at the end.
Categorical Dqn (Bellemare et al., 2017)	Standard deep Q learning agents return a scalar value (representing the q value) for each action. Instead this outputs a probability distribution over action values that is believed to be helpful due to the stochastic nature from the problem (from the agents perspective).
Deep deterministic policy gradient (Silver et al., 2014)	As the action space is continuous, DDPG allows for investigation of the difference between continuous and discrete action spaces of the DQN agents. As policy gradient can be more effective at learning a policy where the reward function is too complex for DQN to model this may give the algorithm another advantage.
Twin delay DDPG (Fujimoto et al., 2018)	Like the Double Dueling DQN agents, TD3 includes a couple new heuristics for the DDPG algorithm. A critic twin is used to prevent the actor network from tricking the critic network, another heuristic is the delaying the updates for actor network compared to the critic network.
D4PG (Barth-Maron et al., 2018)	Like the Categorical DQN algorithm, D4PG adds a heuristic for the critic to output a value distribution that allows for better approximation for environments that are stochastic in nature.

TABLE 4.1: Table of the implemented reinforcement learning algorithms

4.2.2 Agent rewards functions

As explained in the background review for reinforcement learning (section 2.2), the Q values is the estimated discounted reward in the future for an action given a particular state. Therefore the rewards that an agent receives for taking an action is extremely important to enable the agent to learn a predictable reward function. This problem of complex reward functions are a known problem for DQN agent to deal with (Mnih et al., 2013)m policy gradients can deal with this better due its ability directly learning the action policy (Sutton and Barto, 2018).

For the auction, the reward is based on the winning price of the task which is award for the winning action. If the task fails, the reward is instead multiplied by a negative constant in order to discourage the auction agent from bidding on tasks that it wouldn't be able to complete. This reward is awarded at the time step of the auction instead of when the task fails or is completed as this makes the function harder to learn as the auction agent has no control or observations over the resource allocation for a task.
As the price of zero is treated as a non-bid in the auction, the agent gets a reward of zero in order to not penalise the agent. But if the agent does bid on a task however doesn't win, the agent's reward is -0.05 as a way of encouraging the agent to change there bid but not enough to force it to do so.

For resource allocation, the reward function is much simpler than the auction agent's reward function, as it only needs to consider the task being weighted at the time and rewards from other tasks allocated at the same time step. This is as a task must consider its actions in conjunction with the resource requirements of other allocated tasks.
For successfully finishing a task, the reward is 1 while the reward for if the task has failed is -1.5. This makes failing a task more costly than completing a task. But when a task's action is not under consideration, this reward is multiplied by 0.4 as while this rewards impact the task, their value is not as impactful as the reward for the action on a particular task. These rewards don't consider the price payed for the task instead valuing each task equally with the aim of forcing the task allocate resources to finish all tasks not just the valuable ones. Using this information, the reward function is simply the sums the rewards of the finished tasks in the next time step.

4.2.3 Agent training observations

As the agent acts in the environment, the observations that the agent views are stored in an experience replay buffer which allows the agents to train from previous observations. However this is a problem for agent due to the separate agents acting with only during its particular action step. This is outlined in figure 4.1, where an agents next observation is often after subsequent actions by the opposite agent.

For the resource allocation agent, a trick is implemented such that the next observation for the agent is not the actual next resource allocation observation

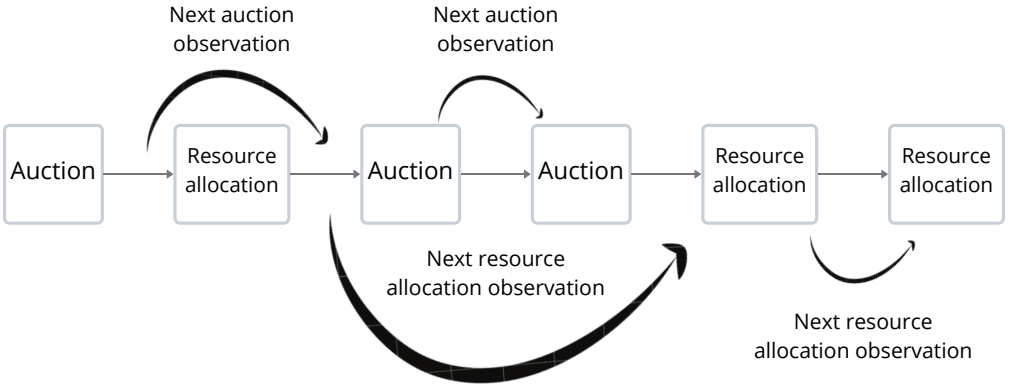

FIGURE 4.1: Environment server agents observations

as shown in figure 4.1 but a generated observation from the resulting server state due to agent's actions. This is identical to the last case in the figure where no auction occurs between resource allocation steps. Because of this, the resource allocation Q value is able to approximate the reward for the results state of its actions directly making it appear to the agent during training that there is no auction steps between the observations and next observations.

For the auction agent, as the agent observations require an auction task to select an action (the task bidding price). A trick like the one implemented for the resource allocation agent can't be to implement. Therefore during training, each server's last observation is recorded, such that when the next auction occurs, this new task observation can be used as the server's next observation in training. This is a suboptimal solution for the agent as the next observation has an unknown number of resource allocation steps resulting in changes to the current allocated tasks. A possible solution that has not been implement in this project is n step prediction (Sutton, 1988). Where the agent doesn't predict the Q value of the next environment, but the value in n steps time. This is believed to possible help reduce the amount of randomness in the server's observations and improve bidding performance.

4.3 Training agents

The first section of this chapter allowed for the simulating MEC servers (section 4.1) as a reinforcement learning environment. While the second section implements auction and resource allocation agents that can interact with the porpoised

environment in order to allow for the train of agents using a range of algorithm outlined in Table 4.1.

Neural networks, the bases of the reinforcement learning agents implemented, often require huge amounts of data and high spec GPUs to run efficiently. Because of this, Iridis 5, University of Southampton supercomputer was utilised with GTX1050 GPUs to train these agents for long periods of time and on mass. During training, for each episode a random environment was generated from a list of possible settings in which the agents would be allocated to random servers. The environment was run till the end, with the agent observation being added to their replay buffers after each actions that were chosen epsilon greedily.

After every 5 episodes, the agents would be evaluated using a set of environment that were pre-generated and saved at the beginning of training. This allows the same environments over training in order to have a constant metric in order to compare the agents over time. The actions taken are recorded to be used in evaluation (chapter **??**) with the number of completed and failed tasks being stored about the resource allocation agent and the winning prices being stored about the auction agents. Plus an action histograms for each agents in order to view how agents bid and weightings are distributed.

4.3.1 Agent training hyperparameters

During training there are a range of hyperparameters for each agent, table 4.2 provides an explanation of value for all of the hyperparameters used in the project.

Agent	**Properties name**	**Value**	**Explanation**
RL Agent	batch_size	32	The number of trajectories from the experience replay buffer that are used each time to train an agent.
RL Agent	error_loss_fn	tf.losses. huber_loss	The loss function for calculating the error that similar the mean squared loss exact has a smaller gradient.

RL Agent	initial_training replay_size	5000	The number of trajectories in the experience replay buffer required before the agent begins training.
RL Agent	training_freq	2	For every trajectory added to the experience replay buffer, for each 2, the agent tries to be trained.
RL Agent	discount_factor	0.9	Within the Q learning function (equation (2.2)), the discount factor determines how important the rewards in the future impact the Q value.
RL Agent	replay_buffer length	25000	The length of the circular experience replay buffer.
RL Agent	save_frequency	25000	The agent networks are saved after 25000 time that agent has been trained
RL Agent	training_loss log_freq	250	Tensorboard allows for data to be saved using training, after every the agent has been trained 250 time, the agents loss is logged for future analysis.
Task Pricing RL Agent	reward_scaling	1	
Task Pricing RL Agent	failed_auction reward	-0.05	The reward for when the agent bids on a task but fails to win the auctioned task.
Task Pricing RL Agent	failed_multiplier	-1.5	A multiplier applied to the winning price is the task fails to be computed within its deadline.
Resource weighting RL Agent	other_task_discount	0.4	The multiplier to tasks not under consideration for a weighting action.

Resource weighting RL Agent	success_reward	1	The reward when the agent successfully completes a task
Resource weighting RL Agent	failed_reward	-1.5	The reward when the agent fails to complete a task within its deadline.
Dqn Agent	target_update_tau	1.0	The update tau value for use in the target update frequency.
Dqn Agent	target_update_freq	2500	The target network in the DQN agent is updated after the agent has been updated 2500 times.
Dqn Agent	initial_epsilon	1	The initial exploration factor during training
Dqn Agent	final_epsilon	0.1	The final exploration factor during training
Dqn Agent	epsilon_steps	10000	The number of training step for linear exploration to move between the initial_epsilon and the final_epsilon factor.
Dueling Dqn Agent	double_loss	True	If to use the double dqn loss function
Categorical Dqn Agent	max_value	-20.0	The maximum value for the value distribution
Categorical Dqn Agent	min_value	25.0	The minimum value for the value distribution
Categorical Dqn Agent	num_atoms	21	The number of atoms for each actions.
Ddpg Agent	actor_learning_rate	0.0001	The learning rate for the optimiser for the actor network.
Ddpg Agent	critic_learning_rate	0.0005	The learning rate for the optimiser for the critic network.

Ddpg Agent	initial_epsilon_std	0.8	The initial exploration standard deviation of the normal distribution used during training
Ddpg Agent	final_epsilon_std	0.05	The final exploration standard deviation of the normal distribution used during training
Ddpg Agent	actor_target update_freq	3000	The actor target network update frequency
Ddpg Agent	critic_target update_freq	1500	The critic target network update frequency
Ddpg Agent	upper_action bound	30.0	The upper action bound for the actor network
Task pricing Ddpg Agent	min_value	-100.0	The minimum value for the critic network to estimate for an action
Task pricing Ddpg Agent	max_value	100.0	The maximum value for the critic network to estimate for an action
Resource allocation Ddpg Agent	min_value	-20	The minimum value for the critic network to estimate for an action
Resource allocation Ddpg Agent	max_value	15	The maximum value for the critic network to estimate for an action
TD3 Agent	actor_update_freq	3	The actor network update frequency for each critic network update.

TABLE 4.2: Agent hyperparameters

Chapter 5

Testing and evaluation

Using the implemented solution from Chapter 4 to test and evaluate its effectiveness, both functional unit tests and agent training evaluation have been designed. To confirm that the environment and agents implemented in the previous chapter (section 4.2) works as intended, unit testing has been added that is explained in Section 5.1. While to evaluate the effectiveness of the proposed solution from Section 3.3, a range of metric have been measured during training in order to test and compare implemented agents, neural network architectures and training parameters. These results are explained in Section 5.2.

5.1 Functional testing

To confirm that the implementation of the agents and environment correctly, PyTest a module within python has been used to design functions are valid. These tests are split into three families: agent, environment and training that are explained in the respective tables 5.1, 5.2 and 5.3. The results from the testing is shown in figure 5.1.

Testing name	**Explanation**
Building agents	Constructs all of the agents with possible arguments to confirm agents can accept of all its attributes
Saving agents	Confirms that agents can successfully save their neural networks and can successfully load the network again and is equal to the agent network.

Agent actions	Confirms that all agents can generate valid actions for both bidding and weighting
Gin config file	Gin is used to set the arguments used during training, to confirm that the file is valid.
Building networks	Constructs all of the neural networks to confirm that the network return a valid output.
Agent epsilon policy	While training, some of the agent actions are randomly selected to train the agents over a large area of the state. This tests that the random actions selected are valid.

TABLE 5.1: Table of testing functions for the agent

Testing name	**Explanation**
Saving and loading an environment	The environment allows for the saving the environment at its current state. This tests that the environment can save and reload the environment successfully.
Loading environment settings	Tests that the load environment settings correctly generates a new random environment based on the settings.
Random action environment steps	To tests that inputs to the auction and resource allocation steps are valid, random actions are generated for the environment, that is repeated for the whole environment.
Auction step	To confirm the Vickrey auction mechanism is completely implemented, a range of possible inputs are tested to confirm that right price and server the task is allocated to.
Resource allocation step	To confirm that servers allocate their resources correct given some inputs.
Allocation of computational resources	Checks that the server correctly allocates computational resources to allocated tasks.
Allocation of storage and bandwidth resources	Checks that the server correctly allocates storage and bandwidth resources to allocated tasks.
Allocation of all resources	Checks that resources are allocated by the server correctly for all of the resources.

TABLE 5.2: Table of testing functions for the environment

Testing name	**Explanation**
Task pricing training	Tests that the task pricing reinforcement learning agents can correctly learning from different auction observations.
Resource allocation training	Tests that resource allocation reinforcement learning agents can correctly learning from different resource allocation observations.
Agent evaluation	Tests that the agent evaluation function for during training correctly captures the correct information due to the actions taken.
Agent training	Tests that agents can be correctly trained over an environment with different actions and observations.
Random actions training	Tests that agents with random actions that can quickly using the environment training methods to confirm that the function work as intended.

TABLE 5.3: Table of testing functions for agent training

5.2 Agent evaluation

In order to compare the implemented agents from Chapter 4, a range of metric are used which are recorded while the agent is training. For the auction agent the metrics are: histogram winning prices, number of no bids, number of failed tasks, number of completed tasks and a histogram of actions taken. For the resource allocation agents the metrics are a histogram of weighting, number of failed tasks and number of completed tasks. Using these metrics evaluation of agent performance can be done between the different reinforcement learning algorithms implemented in Table 4.1, network architectures in Table 3.3 and methods of training different agents.
These evaluations fall into three families: env and agent num, algorithm and network architecture that are analysed in Subsections 5.2.1, 5.2.2 and 5.2.3 respectively.

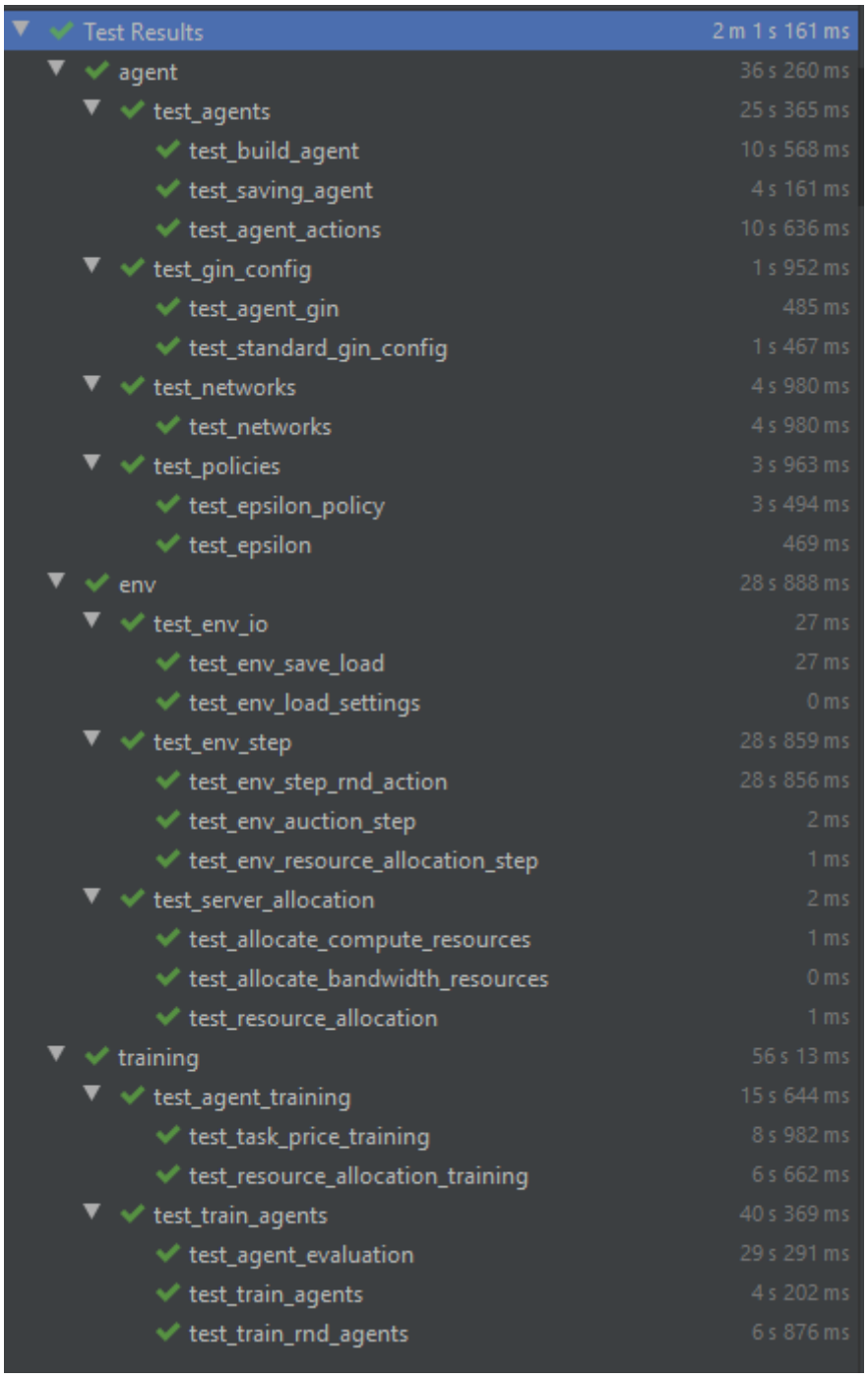

FIGURE 5.1: Results of the unit functions described in the Tables 5.1, 5.2 and 5.3

5.2.1 Environment and Agent number training

The analysis of the different reinforcement learning algorithms and neural network architectures in Subsection 5.2.2 and 5.2.3 respectively assume two qualities that this subsection analyses. These are the training and evaluation environments and the number of agents used during training. As there are huge ranges of

possible environment settings that agents could be trained, investigating agent environment generality is a challenge and an important measure. As in real-life, the environment can be unpredictable and somewhat random meaning that agents must be not overfitted to particular environments used during training.

An advantage of using the Vickrey auction over alternative auctions, explored in Section 3.2, is that it is Incentive compatible. An auction property meaning that the dominant strategy for all agents is to bid truthfully, that is the agent's evaluation of the task. Due to agents not need to learn to "out bid" each other, agent need to learn the true evaluation of a task for themselves. Because of this, another training implemented is that just a single agent is used that is then compared to when multiple agents are trained simultaneously.

During train, every 10 episodes, the agents are trained on the environments pre-generated from all of the multi-env settings. In each of these evaluations, five metrics are collected: the number of completed tasks (figure 5.3), number of failed tasks (figure 5.4), the percentage of tasks attempted (figure 5.5), total prices (figure 5.6) and total winning prices (figure 5.7).

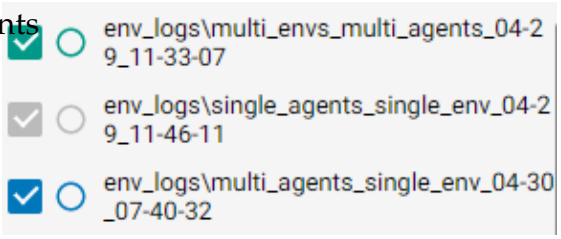

FIGURE 5.2: Environment training legend

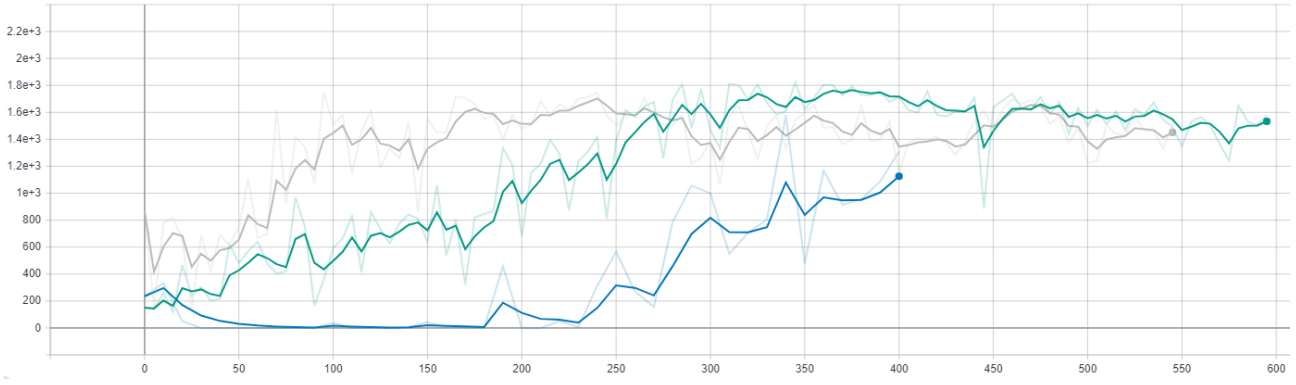

FIGURE 5.3: Number of completed tasks

5.2.2 Reinforcement learning algorithm training

As multiple different reinforcement learning policy outlined in table 4.1, this test compares the results of the different agents against each other.

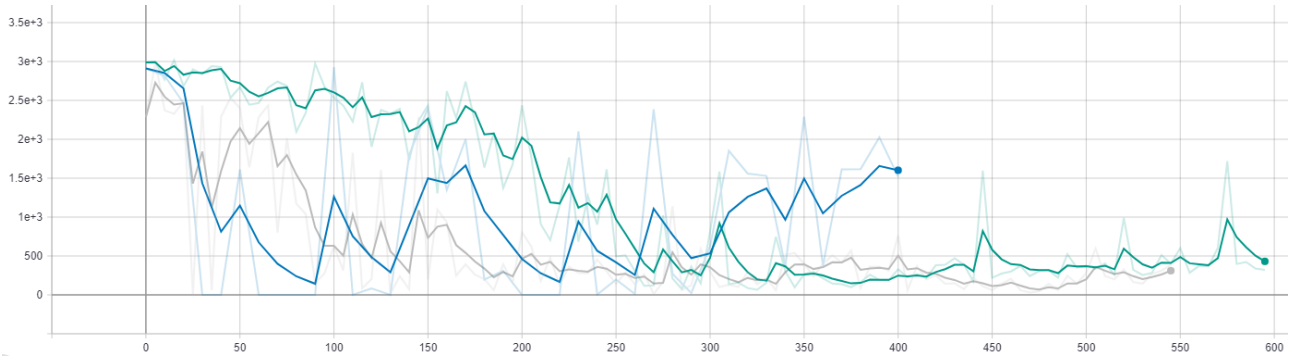

FIGURE 5.4: Number of failed tasks

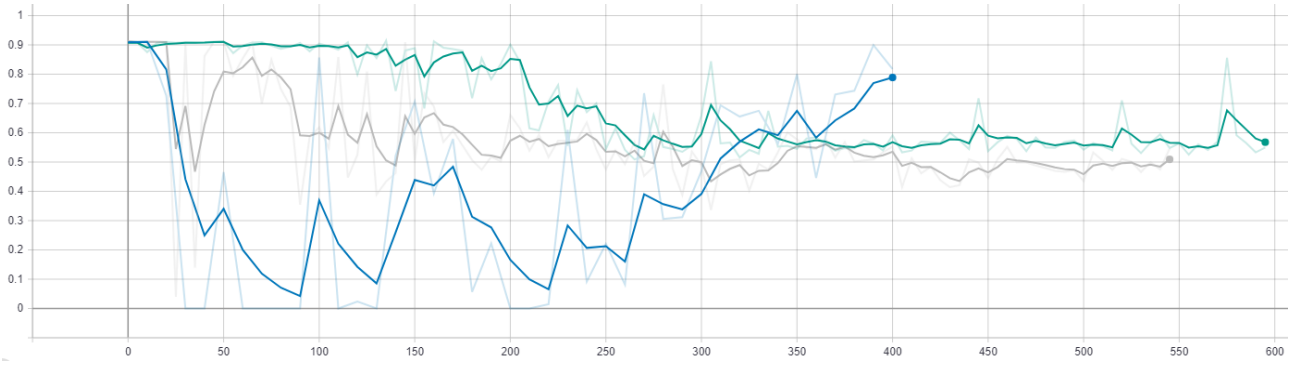

FIGURE 5.5: Percentage of tasks attempted

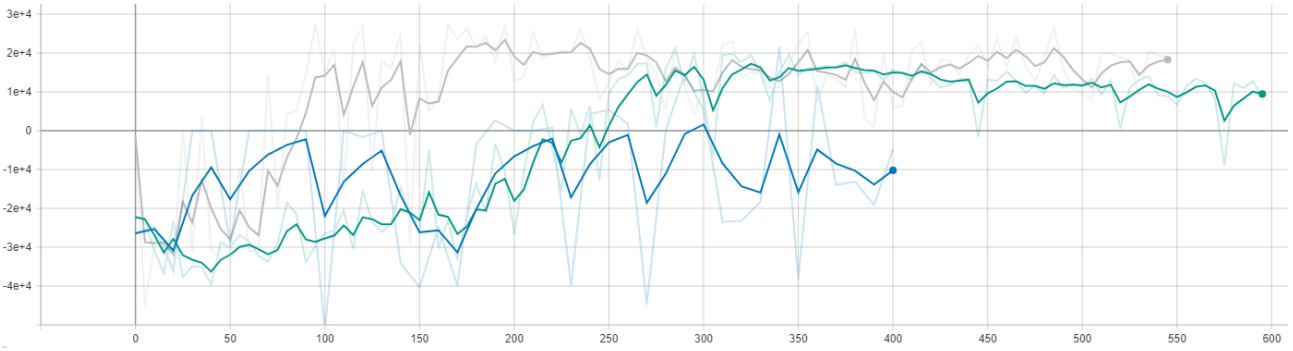

FIGURE 5.6: Total prices

5.2.3 Neural network architecture training

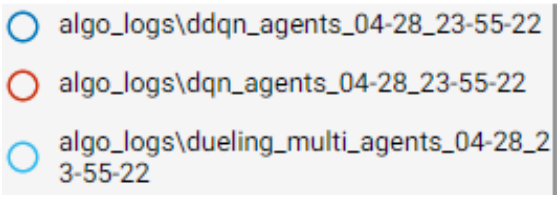

FIGURE 5.14: Environment training legend

There are a wide-range of compatible neural network architectures that agents can use, as outlined in table 3.3. To use these agents, the underlying policies are kept the same with a range of model networks are trained.

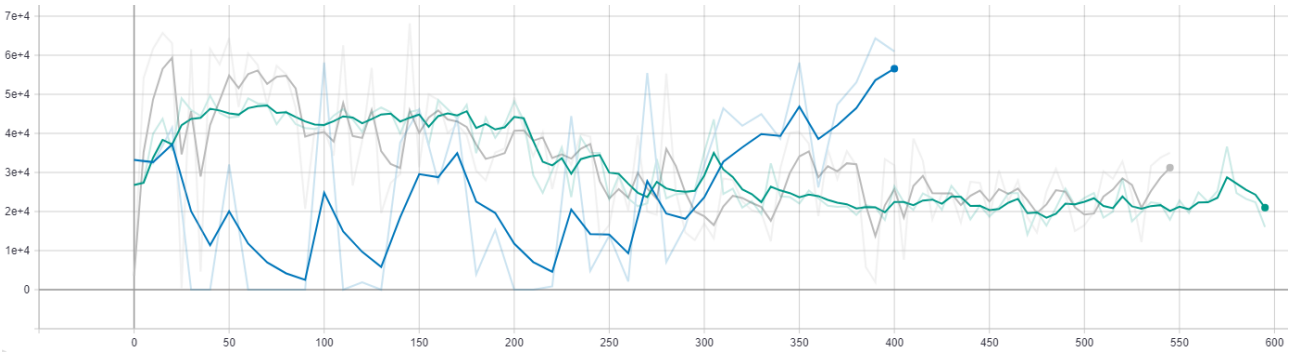

FIGURE 5.7: Total winning prices

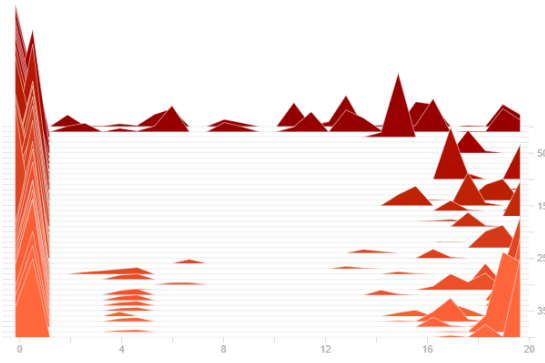

FIGURE 5.8: Multi agent single environment auction prices

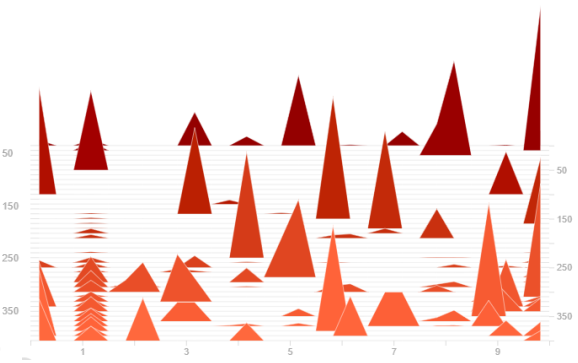

FIGURE 5.9: Multiple agent single environment resource weightings

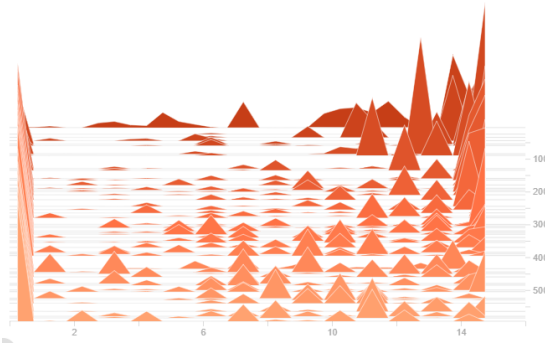

FIGURE 5.10: Multi agent multi environment auction prices

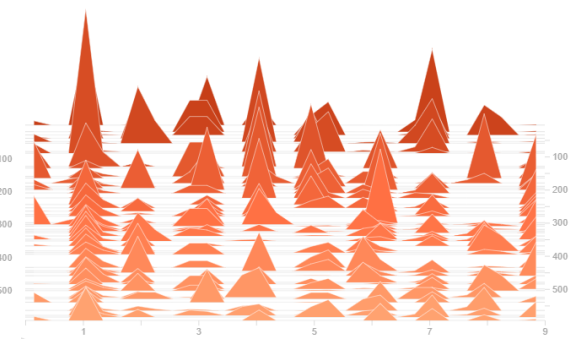

FIGURE 5.11: Multiple agent multi environment resource weightings

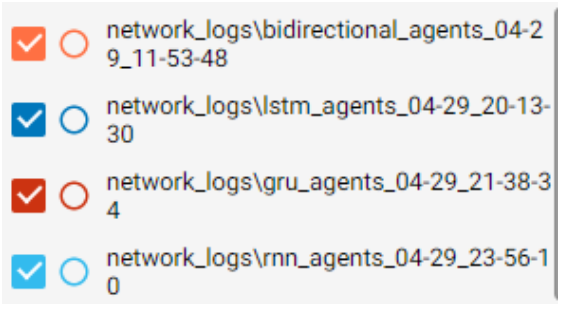

FIGURE 5.26: Environment training legend

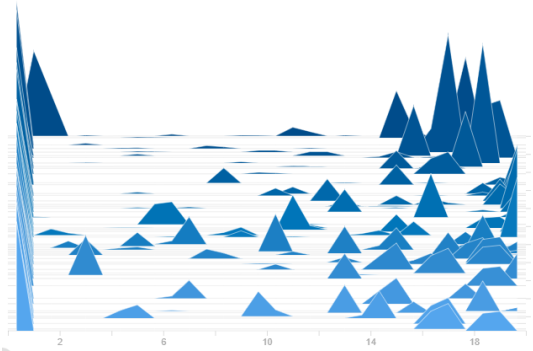

FIGURE 5.12: Single agent single environment auction prices

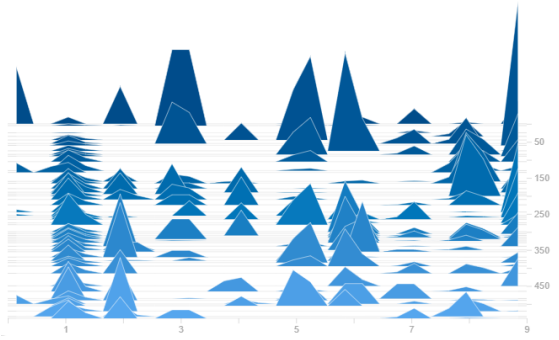

FIGURE 5.13: Multiple agent multi environment resource weightings

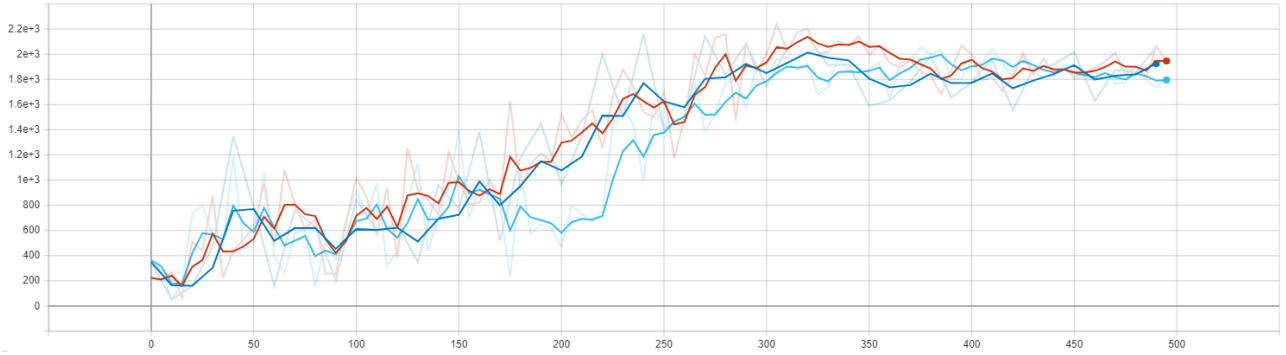

FIGURE 5.15: Number of completed tasks

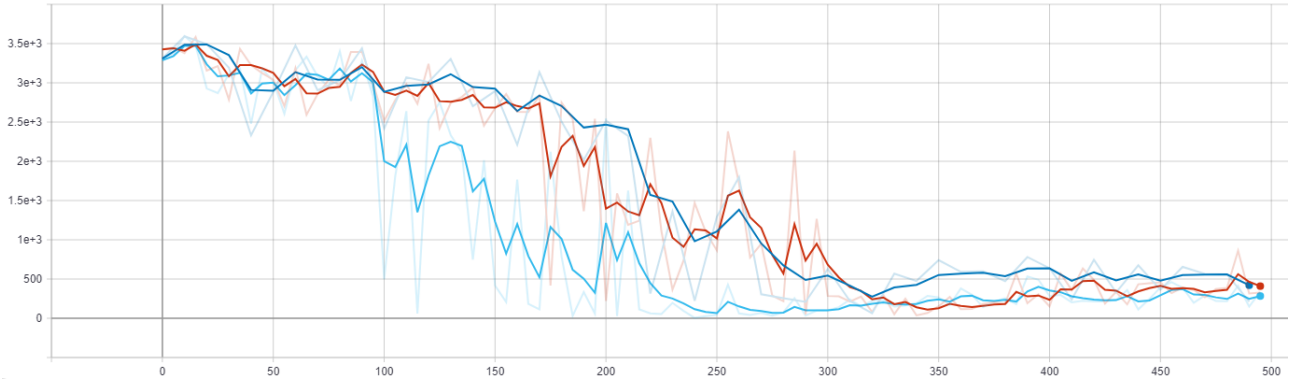

FIGURE 5.16: Number of failed tasks

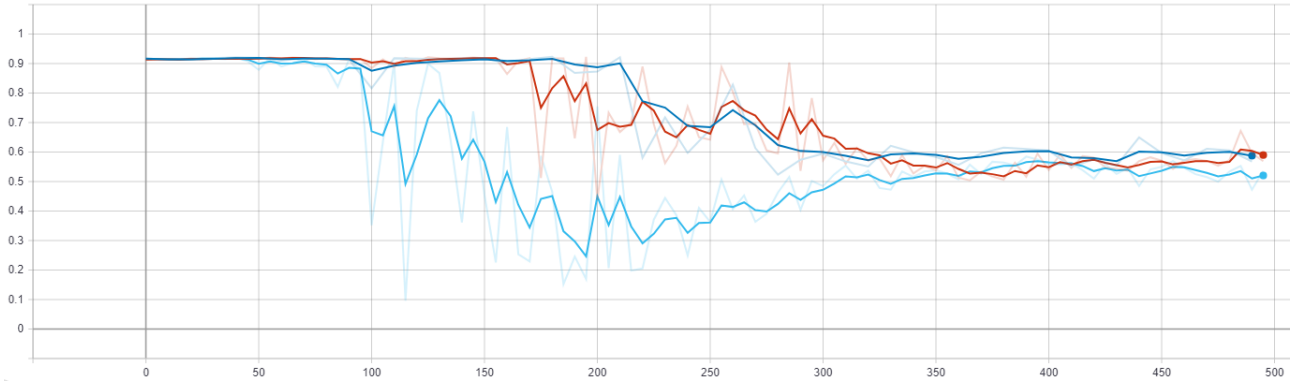

FIGURE 5.17: Percent of tasks attempted

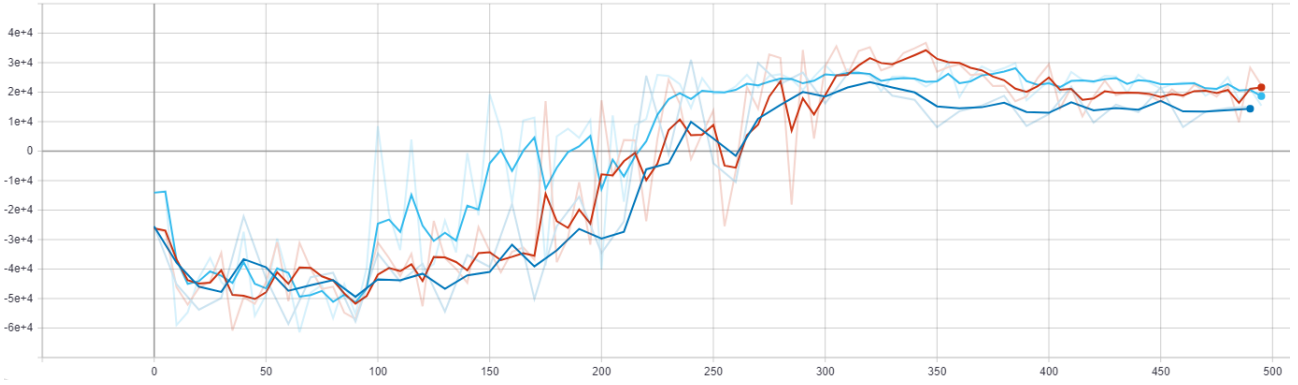

FIGURE 5.18: Total prices

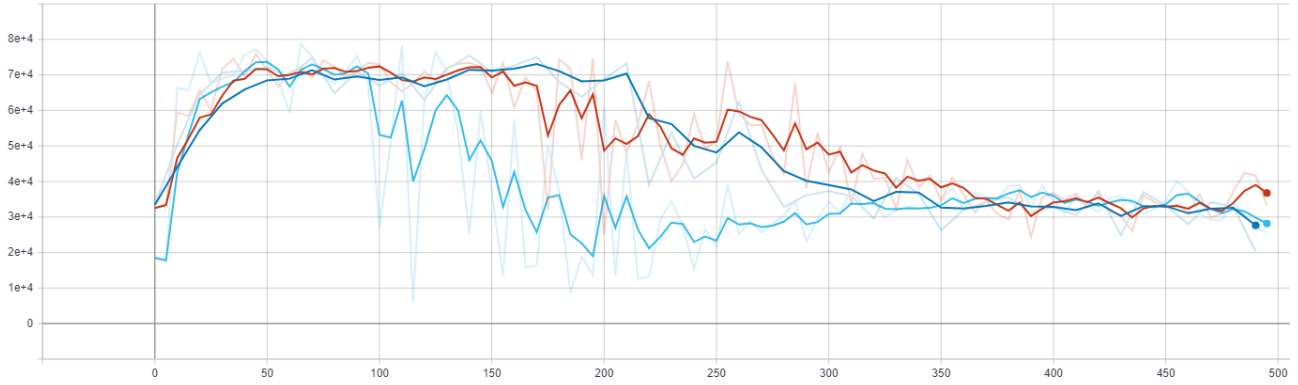

FIGURE 5.19: Winning prices

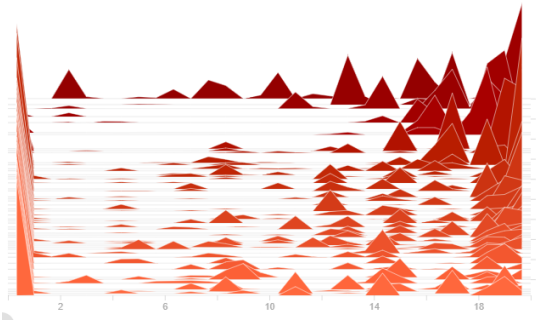

FIGURE 5.20: Deep Q Network auction prices

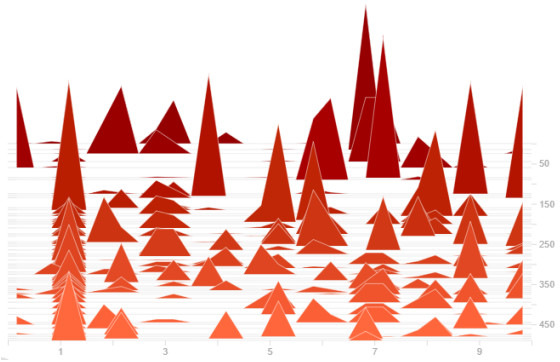

FIGURE 5.21: Deep Q Network resource weightings

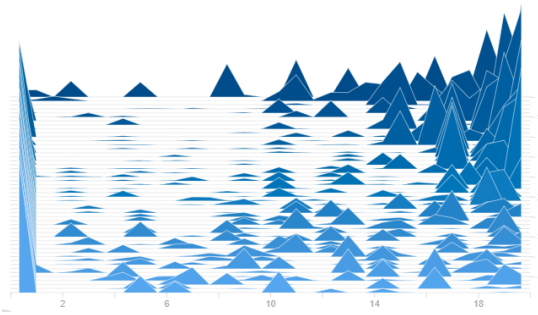

FIGURE 5.22: Double Deep Q Network auction prices

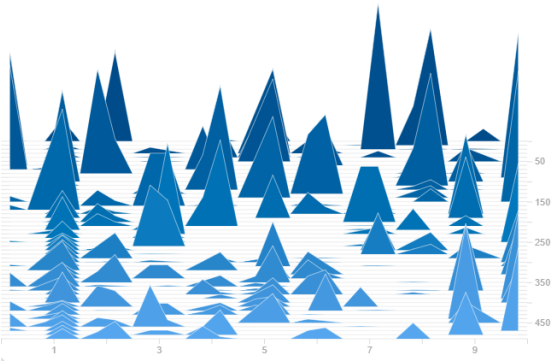

FIGURE 5.23: Double Deep Q Network resource weightings

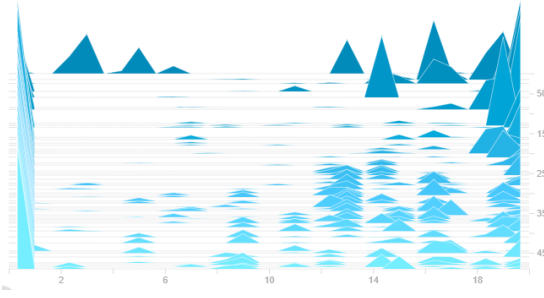

FIGURE 5.24: Dueling Deep Q Network auction prices

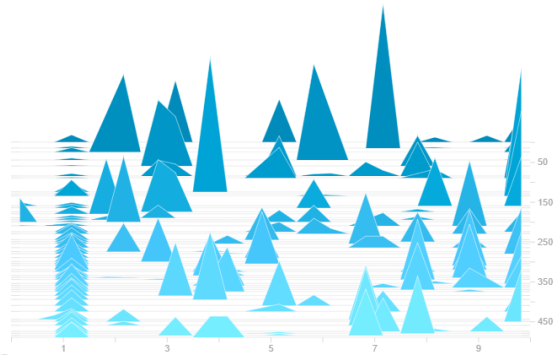

FIGURE 5.25: Dueling Deep Q Network resource weightings

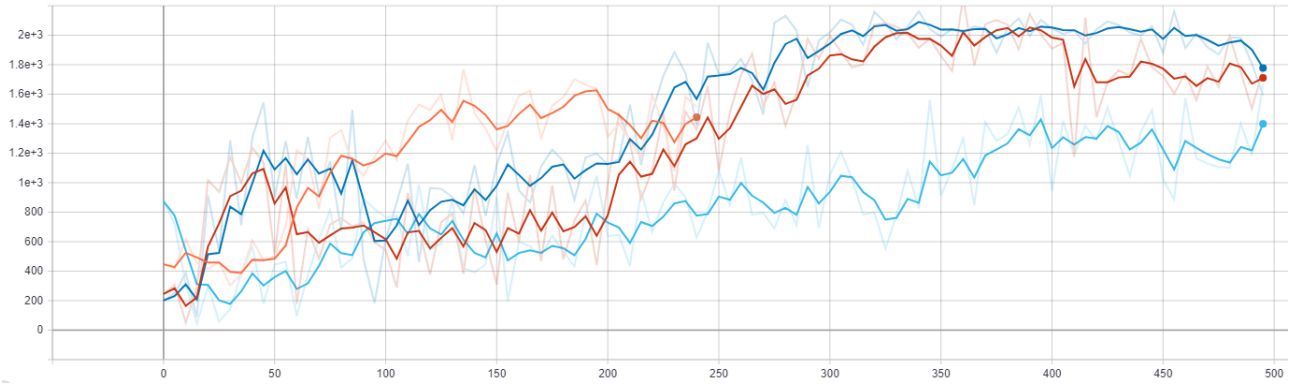

FIGURE 5.27: Number of completed tasks

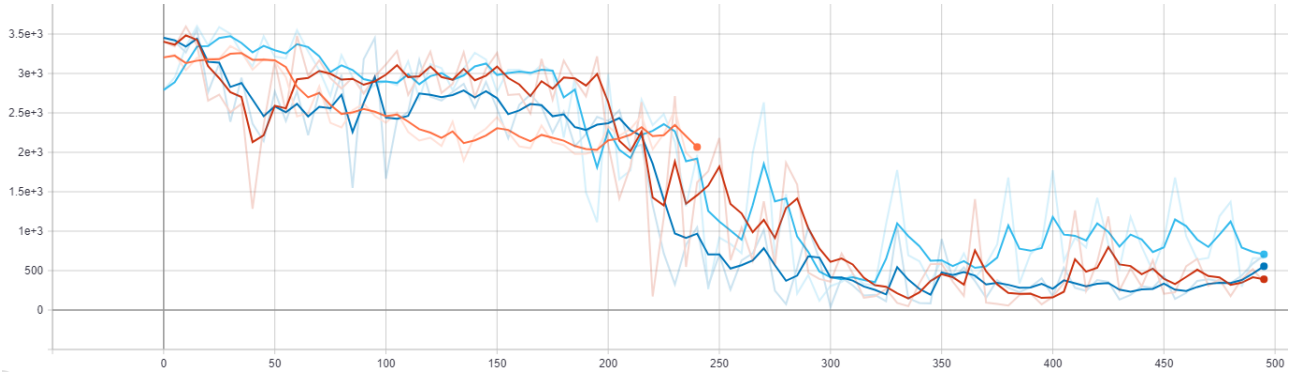

FIGURE 5.28: Number of failed tasks

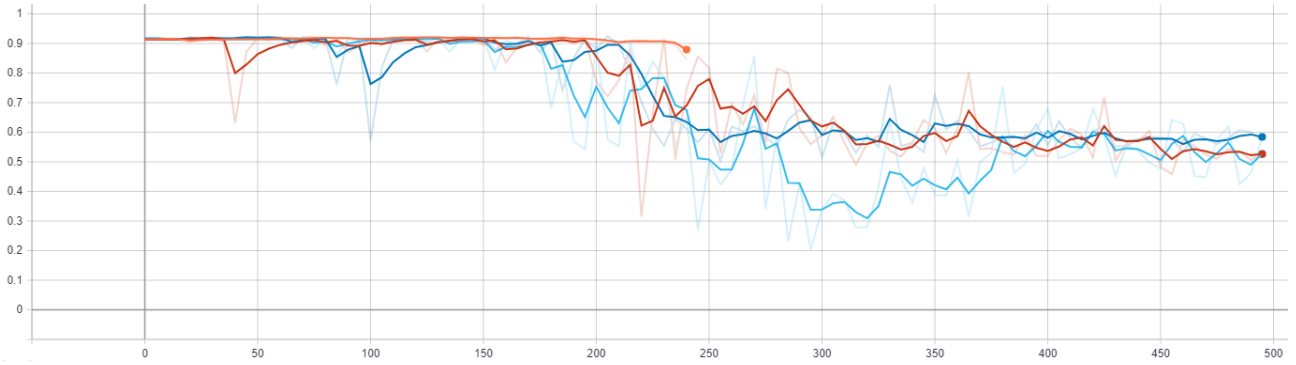

FIGURE 5.29: Percent of tasks attempted

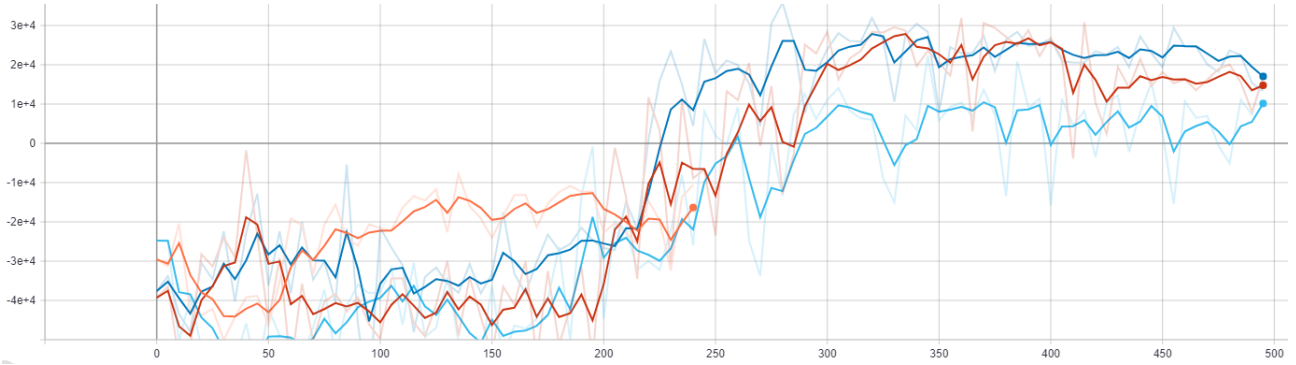

FIGURE 5.30: Total prices

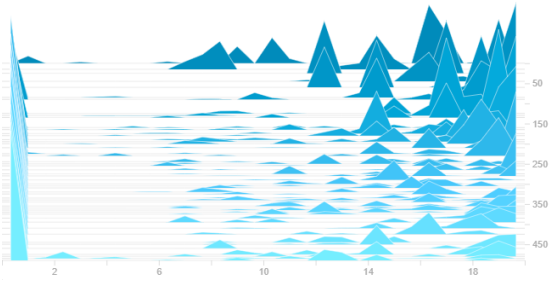

FIGURE 5.31: Rnn network architecture auction prices

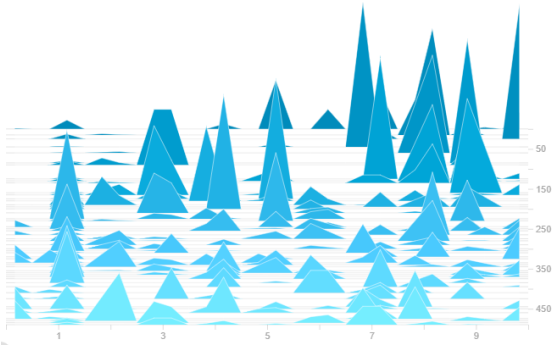

FIGURE 5.32: Rnn network architecture resource weightings

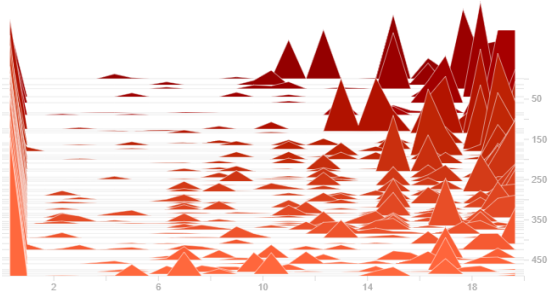

FIGURE 5.33: GRU network architecture auction prices

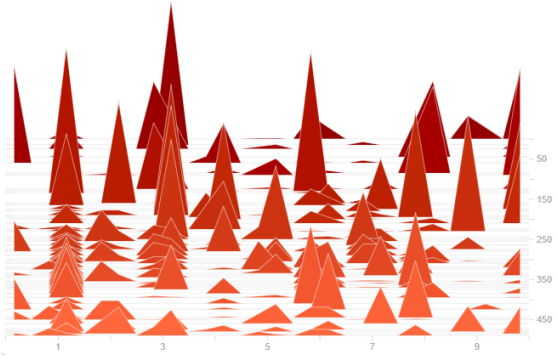

FIGURE 5.34: GRU network architecture resource weightings

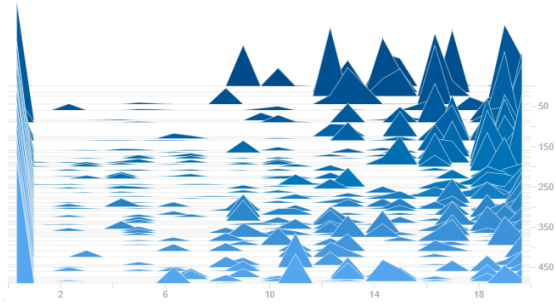

FIGURE 5.35: LSTM network architecture auction prices

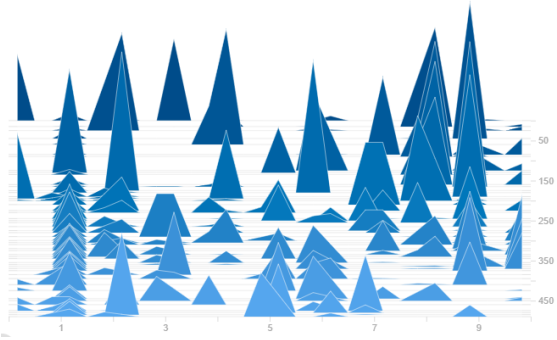

FIGURE 5.36: Rnn network architecture resource weightings

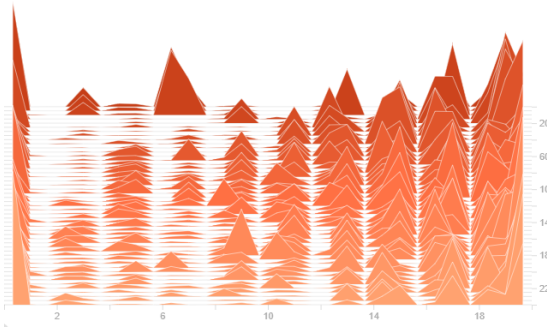

FIGURE 5.37: Bidirectional network architecture auction prices

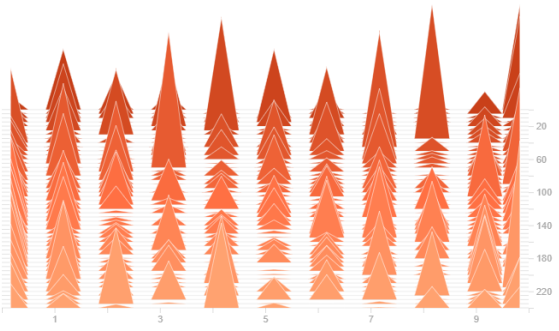

FIGURE 5.38: Bidirectional network architecture resource weightings

Chapter 6

Conclusion and future work

The aim of this project was to expand previous research to fix perceived flaws in the formulation by introducing the notion of time into the resource allocation optimisation model. As a result, a new optimisation problem was presented in Section 3.1 with an auction mechanism proposed as well to deal with self-interested users and to distribute tasks to self-interested servers. To know how to efficiently bid and allocation resources to tasks, reinforcement learning agents were proposed that aimed to learn these policies. An implementation of an MEC environment was developed and numerous reinforcement learning algorithms were used to train both auction and resource weighting agent. These agents were found to efficiently learn an optimal policy however were found to not produce optimal policies such that $\tilde{5}\%$ of all tasks were no completed within there time frame. A range of reasons why this may have occurred in Chapter 5 as a well as policy gradient agents being unable to escape local maxima prevent them from achieving results close to that of the deep Q learning agents. Therefore this project has been viewed as a success however this author believes have more research and analysis of agents is required before such agents can be implemented into real-life systems.

For future work into this project, this author believes that several additions to the agents proposed could greatly improve their performance like n-step rewards (Sutton, 1988) and distributional agents (Bellemare et al., 2017) that would improve Q value estimation within stochastic environment. An additional heuristic for the policy gradient, would be use a centralised critic (Lowe et al., 2017) that has been proposed in mix competitive-cooperative environment to help agents work together.

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Appendix A: Paper

This paper was been produced with the authors being myself, Dr Sebastian Stein, Professor Tim Norman from Southampton University, Dr Fidan Mehmeti, Professor Tom La Porta, Caroline Rubein from Pennsylvania State University and Dr Geeth Demel from IBM and within this project is referred to as Towers et al. (2020).

Auction-based Mechanisms for Allocating Elastic Resources in Edge Clouds

Paper #1263

ABSTRACT

Edge clouds enable computational tasks to be completed at the edge of the network, without relying on access to remote data centres. A key challenge in these settings is the limited computational resources that need to be allocated to many self-interested users. Here, existing resource allocation approaches usually assume that tasks have inelastic resource requirements (i.e., a fixed amount of compute time, bandwidth and storage), that may result in inefficient resource use due to unbalanced requirements. To address this, we propose a novel approach that takes advantage of the elastic nature of some of the resources, e.g., to trade-off computation speed with bandwidth allowing a server to execute more tasks by their deadlines. We describe this problem formally, show that it is NP-hard and then propose a scalable approximation algorithm. To deal with the self-interested nature of users, we show how to design a centralized auction that incentives truthful reporting of task requirements and values. Moreover, we propose novel auction-based decentralized approaches that are not always truthful, but that limit the information required from users and that can be adjusted to trade off convergence speed with solution quality. In extensive simulations, we show that considering the elasticity of resources leads to a gain in utility of around 20% compared to existing fixed approaches and that our novel auction-based approaches typically achieve 95% of the theoretical optimal.

KEYWORDS

Edge clouds; elastic resources; auctions

1 INTRODUCTION

In the last few years, cloud computing [2] has become a popular solution to run data-intensive applications remotely. However, in some application domains, it is not feasible to rely a remote cloud, for example when running highly delay-sensitive and computationally-intensive tasks, or when connectivity to the cloud is intermittent. To deal with such domains, *mobile edge computing* [13] has emerged as a complementary paradigm, where computational tasks are executed at the edge of mobile networks at small data-centers, known as *edge clouds*.

Mobile edge computing is a key enabling technology for the Internet-of-Things (IoT) [6] and in particular applications in smart cities [19] and disaster response scenarios [9]. In these applications, low-powered devices generate computational tasks and data that have to be processed quickly on local edge cloud servers. More specifically, in smart cities, these devices could be smart intersections that collect data from road-side sensors and vehicles to produce an efficient traffic light sequence to minimize waiting times [14]; or it could be CCTV cameras that analyse video feeds for suspicious behaviour, e.g., to detect a stabbing or other crime in progress [20]. In disaster response, sensor data from autonomous vehicles (including video, sonar and LIDAR) can be aggregated in real time to produce maps of a devastated area, search for potential victims and help first responders in focusing their efforts to save lives [1].

To accomplish these tasks, there are typically several types of resources that are needed, including communication bandwidth, computational power and data storage resources [7], and tasks are generally delay-sensitive, i.e., have a specific completion deadline. When accomplished, different tasks carry different values for their owners (e.g., the users of IoT devices or other stakeholders such as the police or traffic authority). This value will depend on the importance of the task, e.g., analysing current levels of air pollution may be less important than preventing a large-scale traffic jam at peak times or tracking a terrorist on the run. Given that edge clouds are often highly constrained in their resources [12], we are interested in allocating tasks to edge cloud servers to maximize the overall social welfare achieved (i.e., the sum of completed task values). This is particularly challenging, because users in edge clouds are typically self-interested and may behave strategically [3] or may prefer not to reveal private information about their values to a central allocation mechanism [18].

An important shortcoming of existing work of resource allocation in edge clouds, e.g., [3, 7], is that it assumes tasks have strict resource requirements — that is, each task consumes a fixed amount of computation (CPU cycles per time), takes up a fixed amount of bandwidth to transfer data and uses up a fixed amount of storage on the server. However, in practice, edge cloud servers have some flexibility in how they allocate limited resources to each task. In more detail, to execute a task, the corresponding data and/or code first has to be transferred to the server it is assigned to, requiring some bandwidth. This then takes up storage on the server. Next, the task needs computing power from the server in terms of CPU cycles per time. Once computation is complete, the results have to be transferred back to the user, requiring further bandwidth. Now, while the the storage capacity at the server for every task is *strict*, since the task cannot be run unless all the data is stored, the bandwidth and compute speed allocated to the task can be *elastic*. This allows flexibility in the resource allocation process enabling resources to be shared evenly, prevent resource self-interested users and for more task to receive service simultaneously.

Against this background, we make the following novel contributions to the state of the art:

- We formulate an optimization problem for assigning the tasks to the servers, whose objective is to maximize total

Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), B. An, N. Yorke-Smith, A. El Fallah Seghrouchni, G. Sukthankar (eds.), May 2020, Auckland, New Zealand

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social welfare, taking into account resource limitations and elastic allocation of resources.
- We prove that the problem is NP-hard and propose an approximation algorithm with a performance guarantee of $\frac{1}{n}$, where n is the number of tasks, and a linearithmic computational complexity, i.e., $O(n \log(n))$.
- We propose a range of auction-based mechanisms to deal with the self-interested nature of users. These offer various trade-offs regarding truthfulness, optimality, scalability, information requirements from users, communication overheads and decentralization.
- Using extensive realistic simulations, we compare the performance of our algorithm against other benchmark algorithms, and show that our algorithm outperforms all of them, while at the same time being within 95% to the optimal solution.

The paper is organized as follows. In the next section we discuss related work. This is followed by the problem formulation in Section 3. Our novel resource allocation mechanisms are presented in Section 4. In Section 5, we evaluate the performance of our mechanisms and compare them against the optimal solution and other benchmarks. Finally, Section 6 concludes the work.

2 RELATED WORK

There is a considerable amount of research in the area of resource allocation and pricing in cloud computing, some of which use auction mechanisms to deal with competition [3, 4, 11, 22]. However, these approaches assume that users request a fixed amount of resources system resources and processing rates, with the cloud provider having no control over the speeds, only the servers that the task was allocated to. In our work, tasks' owners report deadlines and overall data and computation requirements, allowing the edge cloud server to distribute its resources more efficiently based on each task's requirements.

Our problem is related to multidimensional knapsack problems. In particular, Nip et al. [15] consider flexibility in the allocation, with linear constraints that are used for elastic weights. The paper provides a pseudo-polynomial time complexity algorithm for solving this problem to maximize the values in the knapsack. Our problem case is similar to their problem, but our problem has non-linear constraints due to the deadline constraint, so their algorithm cannot be applied here.

Other closely related work on resource allocation in edge clouds [7] considers both the placement of code/data needed to run a specific task, as well as the scheduling of tasks to different edge clouds. The goal there is to maximize the expected rate of successfully accomplished tasks over time. Our work is different both in the setup and the objective function. Our objective is to maximize the value over all tasks. In terms of the setup, they assume that data/code can be shared and they do not consider the elasticity of resources.

3 PROBLEM FORMULATION

In this section we first describe the system model. Then, we present the optimization problem and prove its NP-hardness.

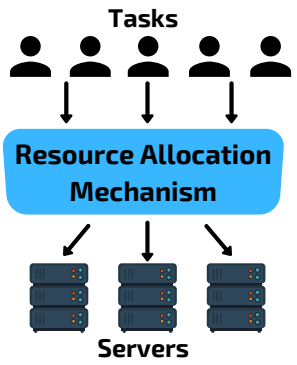

Figure 1: System Model

3.1 System model

A sketch of the system is shown in Fig. 1. We assume that in the system there is a set of servers $I = \{1, 2, \ldots, |I|\}$ servers, which could be edge clouds that can be accessed either through cellular base stations or WiFi access points (APs). Servers have different types of resources: storage for the code/data needed to run a task (e.g., measured in GB), computation capacity in terms of CPU cycles per time interval (e.g., measured in FLOP/s), and communication bandwidth to receive the data and to send back the results of the task after execution (e.g., measured in Mbit/s). We assume that the servers are heterogeneous in all their characteristics. More formally, we denote the storage capacity of server i with S_i, computation capacity with W_i, and the communication capacity with R_i.

There is a set $J = \{1, 2, \ldots, |J|\}$ of different tasks that require service from one of the servers.[1] Every task $j \in J$ has a value v_j that represents the value of running the task to its owner. To run any of these tasks on a server requires storing the appropriate code/data on the same server. These could be, for example, a set of images, videos or CNN layers in identification tasks. The storage size of task j is denoted as s_j with the rate at which the program is transferred to the server being $s_j^{'}$. For a task to be computed successfully, it must fetch and execute instructions on a CPU. We consider the total number of CPU cycles required for the program to be w_j, where the rate at which the CPU cycles are assigned to the task per unit of time is $w_j^{'}$. Finally, after the task is run and the results obtained, the latter need to be sent back to the user. The size of the results for task j is denoted with r_j, and the rate at which they are sent back to the user is $r_j^{'}$. Every task has its deadline, denoted by d_j. This is the maximum time for the task to be completed in order for the user to derive its value. This time includes: the time required to send the data/code to the server, run it on the server, and get back the results. We assume that there is an *all* or *nothing* task execution reward scheme, meaning that for the task value to be awarded the entire task must be run and the results sent back within the deadline.

[1] We focus on a single-shot setting in this paper. In practice, an allocation mechanism would repeat the allocation decisions described here over regular time intervals, with longer-running tasks re-appearing on consecutive time intervals. We leave a detailed study of this to future work.

3.2 Optimization problem

Given the aforementioned assumptions, the optimal assignment of tasks to servers and optimal allocation of resources in a server to the tasks assigned to that server is obtained as a solution to the following optimization problem. Here, the decision variables are $x_{i,j} \in \{0,1\}$ (whether to run task j on server i) as well as $s_j^{'}$, $r_j^{'}$ and $w_j^{'}$ (indicating the bandwidth rates for transferring the code, for returning the results and the CPU cycles per unit of time, respectively).

$$\max \sum_{\forall j \in J} v_j \left(\sum_{\forall i \in I} x_{i,j} \right) \tag{1}$$

s.t.

$$\sum_{\forall j \in J} s_j x_{i,j} \leq S_i, \qquad \forall i \in I, \tag{2}$$

$$\sum_{\forall j \in J} w_j^{'} x_{i,j} \leq W_i, \qquad \forall i \in I, \tag{3}$$

$$\sum_{\forall j \in J} (r_j^{'} + s_j^{'}) \cdot x_{i,j} \leq R_i, \qquad \forall i \in I, \tag{4}$$

$$\frac{s_j}{s_j^{'}} + \frac{w_j}{w_j^{'}} + \frac{r_j}{r_j^{'}} \leq d_j, \qquad \forall j \in J, \tag{5}$$

$$0 \leq s_j^{'} \leq \infty, \qquad \forall j \in J, \tag{6}$$

$$0 \leq w_j^{'} \leq \infty, \qquad \forall j \in J, \tag{7}$$

$$0 \leq r_j^{'} \leq \infty, \qquad \forall j \in J, \tag{8}$$

$$\sum_{\forall i \in I} x_{i,j} \leq 1, \qquad \forall j \in J, \tag{9}$$

$$x_{i,j} \in \{0,1\}, \qquad \forall i \in I, \forall j \in J. \tag{10}$$

The objective (Eq.(1)) is to maximize the total value over all tasks (i.e., the social welfare). Task j will receive the full value v_j only if it is executed entirely and the results are obtained within the deadline for that task. Constraint (Eq.(2)) relates to the finite storage capacity of every server to store code/data for the tasks that are to be run. The finite computation capacity of every server is expressed through Eq.(3), whereas Eq.(4) denotes the constraint on the communication capacity of the servers. As can be seen, the communication bandwidth comprises two parts: one part to send the data/code or request to the server, and the other part to get the results back to the user.[2] Constraint Eq.(5) is the deadline associated with every task, where the total time of the task in the system is the sum of the time to send the request and code/data to the server, time to run the task, and the time it takes the server to send all the results to the user. Note that if a task is not run on any server, this constraint can be satisfied by choosing arbitrarily high bandwidth and CPU rates (without being constrained by the resource limits of any server). The rates at which the code is sent, run and the results are sent back are all positive and finite (Eqs. (6), (7), (8)). Further, every task is served by at most one server (Eq.(9)). Finally, a task is either served or not (Eq.(10)).

[2]Not that sending and receiving data will not always overlap, but for tractability we assume they deplete a common limited bandwidth resource per time step. This ensures that the bandwidth constraint is always satisfied in practice.

Complexity: In the following we show that this optimization problem is NP-hard.

Theorem 3.1. *The optimization problem* (1)-(10) *is NP-hard.*

Proof. The optimization problem without constraint (5) is a 0-1 multidimensional knapsack problem [10], which is a generalization of a simple 0-1 knapsack problem. The latter is an NP-hard problem [10]. Given this, it follows that the 0-1 multidimensional knapsack problem is also NP-hard. Since optimization problem (1)-(10) is a generalization of a 0-1 multidimensional knapsack problem, it follows that it is NP-hard as well. □

Before we propose our novel allocation mechanisms for the allocation problem with elastic resources, we briefly outline an example that illustrates why considering this elasticity is important. In this example, there are 12 potential tasks and 3 servers (the exact settings can be found in table 2 for the tasks and table 1 for the servers).

Figure 2 shows the best possible allocation if tasks have fixed resource requirements. The resource speeds were chosen such to the minimum total resource usage that the task would require from the deadline. Here, 9 of the tasks are run, resulting in a total social welfare of 980 due to the limitation of the server's computation and the task requirement not being balanced.

In contrast to this, Figure 3 depicts the optimal allocation if elastic resources are considered. Here, it is evident that all of the resources are used by the servers whereas the fixed (in figure 2) cant do this. In total, the elastic approach manages to schedule all 12 tasks within the resource constraints, achieving a total social welfare of 1200 (an 19% improvement over the fixed approach).

The figures represent resource usage of the servers by the three bars relating to each of this resources (storage, CPU and bandwidth). For each task that is allocated to the server, the percentage of the resource's used is bar size. Then, for the tasks that are assigned to corresponding servers, the percentage of used resources are also depicted.

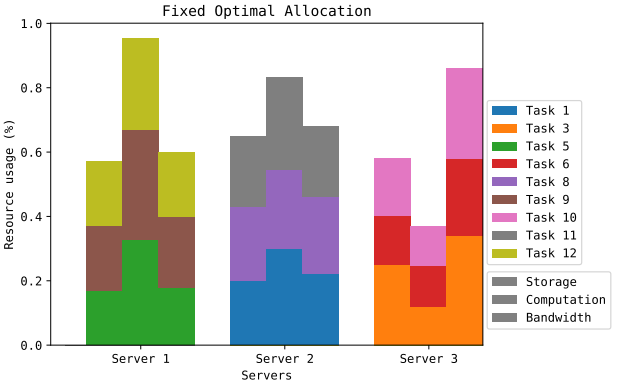

Figure 2: Optimal solution with fixed resources. Due to not being able to balance out the resources, bottlenecks on the server 1 and 2's computation have occurred

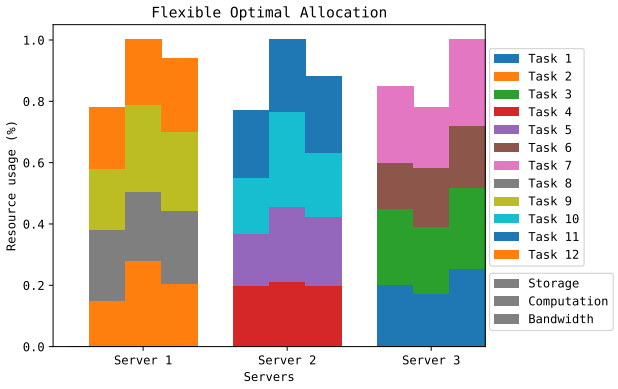

Figure 3: Optimal solution with elastic resources. Compared to the fixed allocation, the elastic allocation is able to fully use all of its resources

Name	S_i	W_i	R_i
Server 1	400	100	220
Server 2	450	100	210
Server 3	375	90	250

Table 1: Servers - Table of server attributes

Name	v_j	s_j	w_j	r_j	d_j	$s_j^{'}$	$w_j^{'}$	$r_j^{'}$
Task 1	100	100	100	50	10	30	27	17
Task 2	90	75	125	40	10	22	32	15
Task 3	110	125	110	45	10	34	30	17
Task 4	75	100	75	35	10	27	21	13
Task 5	125	85	90	55	10	24	28	17
Task 6	100	75	120	40	10	20	32	16
Task 7	80	125	100	50	10	31	30	19
Task 8	110	115	75	55	10	30	22	20
Task 9	120	100	110	60	10	27	29	24
Task 10	90	90	120	40	10	25	30	17
Task 11	100	110	90	45	10	30	26	16
Task 12	100	100	80	55	10	24	24	22

Table 2: Tasks - Table of task attributes, the columns for resource speeds ($s_j^{'}, w_j^{'}, r_j^{'}$) is for fixed speeds which the flexible allocation does not take into account. The fixed speeds is the minimum required resources to complete the task within the deadline constraint.

4 FLEXIBLE RESOURCE ALLOCATION MECHANISMS

In this section, we propose several mechanisms for solving the resource allocation problem with elastic resources. First, we discuss a centralized greedy algorithm (detailed in Section 4.1) with a $\frac{1}{|J|}$ performance guarantee and polynomial run-time. Then, we consider settings where task users are self-interested and may either report their task values and requirements strategically or may wish to limit the information they reveal to the mechanism. To deal with such cases, we propose two auction-based mechanisms, one of which can be executed in a decentralized manner (in Sections 4.2 and 4.3).

4.1 Greedy Mechanism

As solving the allocation problem with elastic resources is NP-hard, we here propose a greedy algorithm (Algorithm 1) that considers tasks individually, based on an appropriate prioritisation function.

More specifically, the greedy algorithm does this in two stages; the first sorts the tasks and the second allocates them to servers. A value density function is applied to each of the task based on its attributes: value, required resources and deadlines. Stage one uses this function to sort the list of tasks. The second stage then iterates through the tasks in the given order, applying two heuristics to each task: one to select the server and another to allocate resources. The first of these heuristics, called the server selection heuristic, works by checking if a server could run the task if all of its resources were to be used for meeting the deadline constraint (eq 5) then calculating how good it would be for the job to be allocated to the server. The second heuristic, called the resource allocation heuristic, finds the best permutations of resources to minimise a formula, i.e., the total percentage of server resources used by the task.

In this paper we prove that the lower bound of the algorithm is $\frac{1}{|J|}$ (where $|J|$ is the number of jobs) using the value of a task as the value density function and using any feasible server selection and resource allocation heuristic. However we found that the task value heuristic is not the best heuristic as it does not consider the effect of the deadline or resources used for a job. In practice, the following heuristic often works better: $\frac{v_j \cdot (s_j + w_j + r_j)}{d_j}$. For the server selection heuristic we use $argmin_{\forall i \in I} S_i^{'} + W_i^{'} + R_i^{'}$, where $S_i^{'}$, $W_i^{'}$, $R_i^{'}$ are the server's available storage, computation and bandwidth resources respectively. While for the resource allocation heuristic we use $min \frac{W_i^{'}}{w_j} + \frac{R_i^{'}}{s_j^{'} + r_j^{'}}$.

Theorem 4.1. *The lower bound of the greedy mechanism is $\frac{1}{n}$ of the optimal social welfare*

Proof. Taking the value of a task as the value density function, the first task allocated will have a value of at least $\frac{1}{n}$ total values of all jobs. As the allocation of resources for a task is not optimal, allocation of subsequent tasks is not guaranteed. Therefore, as the optimal social welfare must be the total values of all jobs or lower then the lower bound of the mechanism must be $\frac{1}{n}$ of the optimal social welfare. □

In figure 4, an example allocation using the algorithm is shown using the model from tables 1 and 2. The algorithm uses the recommend heuristic proposed above and allows for all tasks to be allocated achieving 100% of the flexible optimal in figure 3.

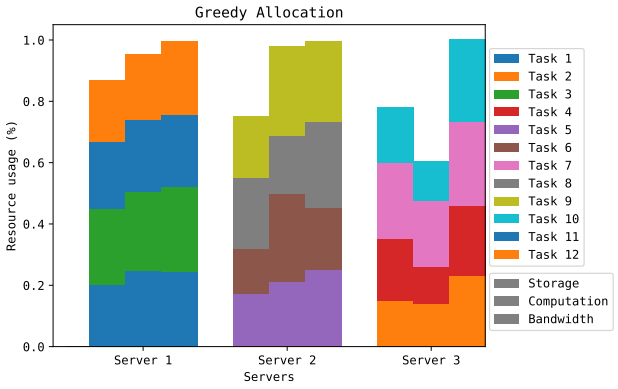

Figure 4: Example Greedy allocation using model from table 2 and 1

Algorithm 1 Greedy Mechanism

Require: J is the set of tasks and I is the set of servers
Require: $S_i^{'}, W_i^{'}$ and $R_i^{'}$ is the available resources (storage, computation and bandwidth respectively) for server i.
Require: $\alpha(j)$ is the value density function of a task
Require: $\beta(j, I)$ is the server selection function of a task and set of servers returning the best server, or $\emptyset$ if the task is not able to be run on any server
Require: $\gamma(j, i)$ is the resource allocation function of a task and server returning the loading, compute and sending speeds
Require: $sort(X, f)$ is a function that returns a sorted list of elements in descending order, based on a set of elements and a function for comparing elements
$J^{'} \leftarrow sort(J, \alpha)$
for all $j \in J^{'}$ **do**
  $i \leftarrow \beta(j, I)$
  if $i \neq \emptyset$ **then**
    $s_j^{'}, w_j^{'}, r_j^{'} \leftarrow \gamma(j, i)$
    $x_{i,j} \leftarrow 1$
  end if
end for

Theorem 4.2. *The time complexity of the greedy algorithm is $O(|J|\,|I|)$, where $|J|$ is the number of tasks and $|I|$ is the number of servers. Assuming that the value density and resource allocation heuristics have constant time complexity and the server selection function is $O(|I|)$.*

Proof. The time complexity of the stage 1 of the mechanism is $O(|J| \log(|J|))$ due to sorting the tasks and stage 2 has complexity $O(|J|\,|I|)$ due to looping over all of the tasks and applying the server selection and resource allocation heuristics. Therefore the overall time complexity is $O(|J|\,|I| + |J| \log(|J|)) = O(|J|\,|I|)$. □

4.2 Critical Value Auction

Due to the problem case being non-cooperative, if the greedy mechanism was used to allocate resources such that the value is the price paid. This is open to manipulation and misreporting of task attributes like the value, deadline or resource requirements. Therefore in this section we propose an auction that is weakly-dominant for tasks to truthfully report it attributes.

Single-Parameter domain auctions are extensively studied in mechanism design [16] and are used where an agent's valuation function can be represented as single value. The task price is calculated by finding the task's value such that if the value were any smaller, the task could not be allocated. This value is called the critical value. This has been shown to be a strategyproof [17] (weakly-dominant incentive compatible) auction so it is a weakly-dominant strategy for a task to honestly reveal its value.

The auction is implemented using the greedy mechanism from section 4.1 to find an allocation of tasks using the reported value. Then for each task allocated, the last position in the ordered the task list such that the task would still allocated is found. The critical value of the task is then equal to the inverse of the value density function where the density is the density of the next task in the list after that position.

In order that the auction is strategyproof, the value density function is required to be monotonic so that misreporting of any task attributes will result in the value density decreasing. Therefore a value density function of the form $\frac{v_j d_j}{\alpha(s_j, w_j, r_j)}$ must be used so that the auction is strategyproof.

Theorem 4.3. *The value density function $\frac{v_j d_j}{\alpha(s_j, w_j, r_j)}$ is monotonic for task j assuming the function $\alpha(s_j, w_j, r_j)$ is monotonic decreasing.*

Proof. In order to misreport the task private value and deadline must be less than the true value. The opposite is true for the required resources (storage, compute and result data) with the misreported value being greater than the true value. Therefore the α function will increase as the resource requirements increase as well, meaning that density will decrease. □

4.3 Decentralised Iterative Auction

VCG (Vickrey-Clark-Grove) auction [21] [5] [8] is proven to be economically efficient, budget balanced and incentive compatible. A task's price is found by the difference of the social welfare for when the task exists compared to the social welfare when the task doesn't exist. Our auction uses the same principle for pricing by finding the difference between the current server revenue and the revenue when the task is allocated (at £0).

The auction iteratively lets a task advertise its requirements to all of the servers who respond with their price for the task. This price is equal to the server's current revenue minus the solution to the the problem in section 4.3.1 plus a small value called the price change variable. Being the reverse of the VCG mechanism, such that the price is found for when the task exists rather than when it doesn't exist. The price change variable allows for the increase in the revenue of the server and is can be chosen by the server. Once all of the server have responded, the task can compare the minimum server price to its private value. If the price is less then the task will accept the servers with the minimum price offer, otherwise the task will stop looking as the price for the task to run on any server is greater than its reserve price.

To find the optimal revenue for a server m given a new task p and set of currently allocated tasks N has a similar formulation to section 3.2. With an additional variable is considered, a task's price being p_n for task n.

4.3.1 Server problem case.

$$\max \sum_{\forall n \in N} p_n x_n \tag{11}$$

$$\text{s.t.} \tag{12}$$

$$\sum_{\forall n \in N} s_n x_n + s_p \leq S_m, \tag{13}$$

$$\sum_{\forall n \in N} w_n^{'} x_n + w_p \leq W_m, \tag{14}$$

$$\sum_{\forall n \in N} (r_n^{'} + s_n^{'}) \cdot x_n + (r_p^{'} + s_p^{'}) \leq R_m, \tag{15}$$

$$\frac{s_n}{s_n^{'}} + \frac{w_n}{w_n^{'}} + \frac{r_n}{r_n^{'}} \leq d_n, \qquad \forall n \in N \cup \{p\}, \tag{16}$$

$$0 \leq s_n^{'} \leq \infty, \qquad \forall n \in N \cup \{p\} \tag{17}$$

$$0 \leq w_n^{'} \leq \infty, \qquad \forall n \in N \cup \{p\} \tag{18}$$

$$0 \leq r_n^{'} \leq \infty, \qquad \forall n \in N \cup \{p\} \tag{19}$$

$$x_n \in \{0, 1\}, \qquad \forall n \in N \tag{20}$$

The objective (Eq.(11)) is to maximize the price of all tasks (not including the new task as the price is zero). The server resource capacity constraints are similar to the constraints in the standard model set out in section 3.2 however with the assumption that the task k is running so there is no need to consider if the task is running or not. The deadline and non-negative resource speeds constraints (5, 6, 7 and 8) are all the same equation with the new task included with all of the other tasks. The equation to check that a task is only allocated to a single server is not included as only server i considers the task k's price.

In auction theory, four properties are considered: Incentive compatible, budget balanced, economically efficient and individual rationality.

- Budget balanced - Since the auction is run without an auctioneer, this allows for the auction to be run in a decentralised way resulting in no "middlemen" taking some money so all revenue goes straight to the servers from the tasks
- Individually Rational - As the server need to confirm with the task if it is willing to pay an amount to be allocated, the task can check this against its secret reserved price preventing the task from ever paying more than it is willing
- Incentive Compatible - Misreporting can give a task as if the task can predict the allocation of resources from server to tasks then tasks can misreport so to be allocate to a certain server that otherwise would result in the task being unallocated.
- Economic efficiency - At the begin then task are almost randomly assigned in till server become full and require kicking tasks off, this means that allocation can fall into a local price maxima meaning that the server will sometime not be 100% economically efficient.

Algorithm 2 Decentralised Iterative Auction

Require: I is the set of servers
Require: J is the set of unallocated tasks, which initial is the set of all tasks to be allocated
Require: $P(i,k)$ is solution to the problem in section 4.3.1 using the server i and new task k. The server's current tasks is known to itself and its current revenue from tasks so not passed as arguments.
Require: $R(i,k)$ is a function returning the list of tasks not able to run if task k is allocated to server i
Require: $\leftarrow_R$ will randomly select an element from a set

```
while |J| > 0 do
    j ←_R J
    p, i ← argmin_{i∈I} P(i, j)
    if p ≤ v_j then
        p_j ← p
        x_{i,j} ← 1
        for all j' ∈ R(i, j) do
            x_{i,j'} ← 0
            p_j' ← 0
            J ← J ∪ j'
        end for
    end if
    J ← J \ {j}
end while
```

The algorithm 2 is a centralised version of the decentralised iterative auction. It works through iteratively checking a currently unallocated job to find the price if the job was currently allocated on a server. This is done through first solving the program in section 4.3.1 which calculates the new revenue if the task was forced to be allocated with a price of zero. The task price is equal to the current server revenue − new revenue with the task allocated + a price change variable to increase the revenue of the server. The minimum price returned by $P(i,k)$ is then compared to the job's maximum reserve price (that would be private in the equivalent decentralised algorithm) to confirm if the job is willing to pay at that price. If the job is willing then the job is allocated to the minimum price server and the job price set to the agreed price. However in the process of allocating a job then the currently allocated jobs on the server could be unallocated so these jobs allocation's and price's are reset then appended to the set of unallocated jobs.

4.4 Attributes of proposed algorithms

In table 3, the important attributes for the proposed algorithm

Attribute	GM	CVA	DIA
Truthfulness		Yes	No
Optimality	No	No	No
Scalability	Yes	Yes	No
Information requirements from users	All	All	Not the reserve value
Communication over heads	Low	Low	High
Decentralisation	No	No	Yes

Table 3: Attributes of the proposed algorithms: Greedy mechanism (GM), Critical Value auction(CVA) and Decentralised Iterative auction (DIA)

5 EMPIRICAL EVALUATION

To test the algorithms presented in section 4, synthetic models have been used to generate a list of tasks and servers.

The synthetic models have been handcrafted with each attribute being generated from a gaussian distribution with a mean and standard deviation.

To compare the greedy algorithm to the optimal elastic allocation, a branch and bound was implemented to solve the problem in section 3.2. In order to compare to fixed speed equivalent models, the minimum total resource required to run the job is found and set as the resource speeds for all of the tasks, with the optimal solution for running the job with the fixed speeds is found as well. To implement the greedy mechanism, the value density function was $\frac{v_j}{s_j+w_j+r_j}$, server selection was $argmin_{\forall i \in I} S_i^{'} + W_i^{'} + R_i^{'}$ and the resource allocation was $mins_j^{'} + w_j^{'} + r_j^{'}$ for job j and servers I.

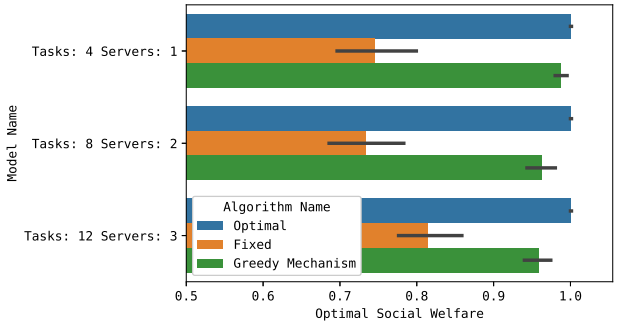

Figure 5: Comparison of the social welfare for the greedy mechanism, optimal, relaxed problem, time limited branch and bound

As figure 5 shows, the greedy mechanism achieves 98% of the optimal solution for the small models, the mechanism achieves within 95% for larger models. In comparison, the fixed allocation achieves 80% of the optimal solution and always does worse than the social welfare of the greedy mechanism.

Figure 6 compares the social welfare of the auction mechanisms: vcg, fixed resource speed vcg, critical value auction and the decentralised iterative auction with different price change variables.

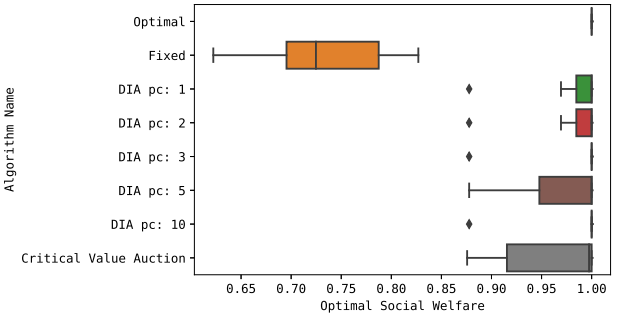

Figure 6: Comparison of the social welfare for the auction mechanisms

VCG is an economically efficient auction that requires the optimal solution to the problem in section 3.2.

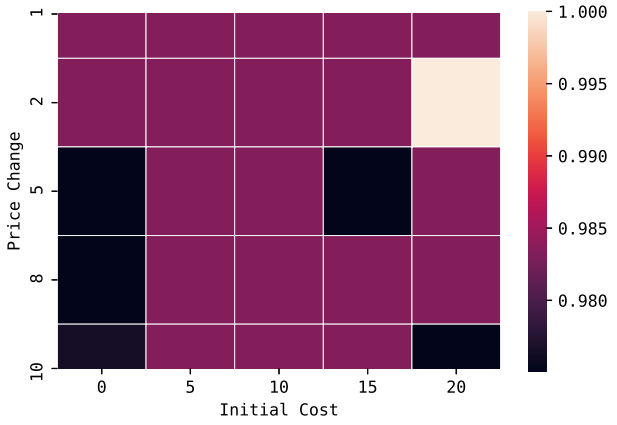

Figure 7: Average number of rounds with a price change variables and task initial cost

Within the context of edge cloud computing, the number of rounds for the decentralised iterative auction is important to making it a feasible auction as it is proportional to the time required to run. We investigated the effect of two heuristic on the number of rounds and social welfare of the auction; the price change variable and initial cost heuristic. With an auction using as minimum heuristic values for the price change and initial cost, figure 7, on average 400 rounds were required for the price to converge while an auction using a price change of 10 and initial cost of 20 means that only on average 80 rounds are required, 5x less. But by using high initial cost and price change heuristics, this can prevent tasks from being allocated, figure 8, shows that the difference in social welfare is only 2% from minimum to maximum heuristics.

6 CONCLUSIONS

In this paper, we studied a resource allocation problem in edge clouds, where resources are elastic and can be allocated to tasks at varying speeds to satisfy heterogeneous requirements and deadlines.

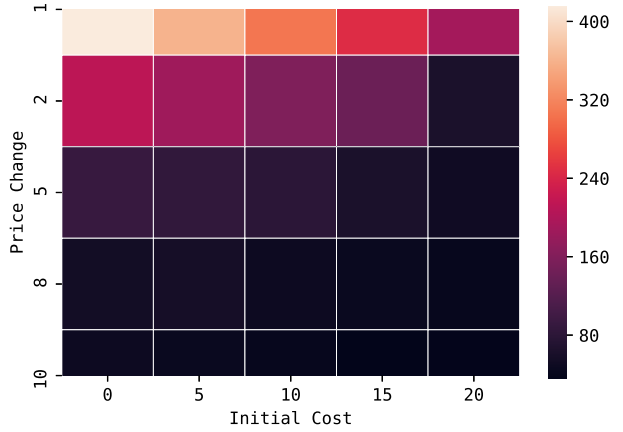

Figure 8: Average social welfare with a price change variables and task initial cost

To solve the problem, we proposed a centralized greedy mechanism with a guaranteed performance bound, and a number of auction-based mechanisms that also consider the elasticity of resources and limit the potential for strategic manipulation. We show that explicitly taking advantage of resource elasticity leads to significantly better performance than current approaches that assume fixed resources.

In future work, we plan to consider the dynamic scenario where tasks arrive and depart from the system over time, and to also consider the case where task preemption is allowed.

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Appendix B: SPIE Presentation

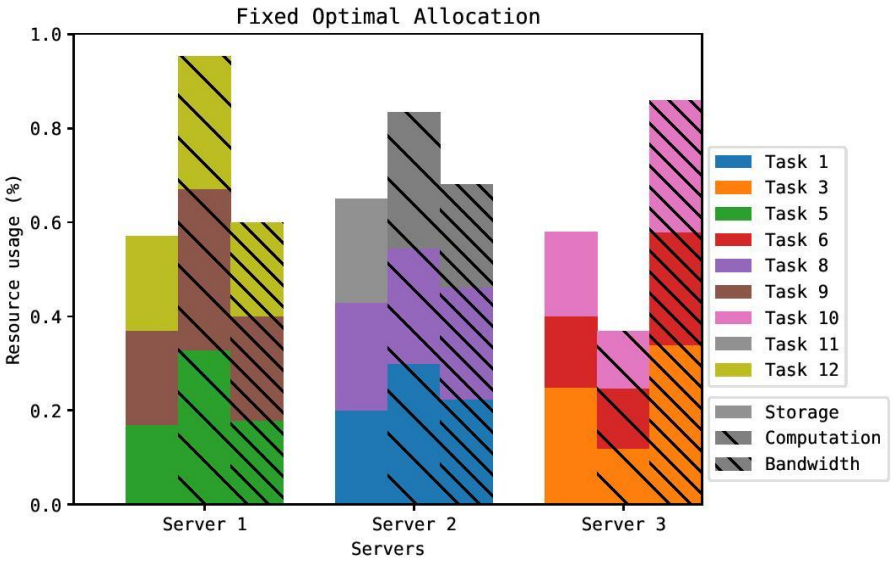
This presentation was produced from the same work as the Towers et al. (2020) with the title ”Analytical agility at the edge of the network through auction mechanisms” at was submitted to the conference on Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications II, as part of the SPIE Defense + Commercial Sensing.

Analytical agility at the edge of the network through auction mechanisms

By Mark Towers, Fidan Mehmeti, Sebastian Stein, Tim Norman, Tom La Porta, Caroline Rublein and Geeth De Mel

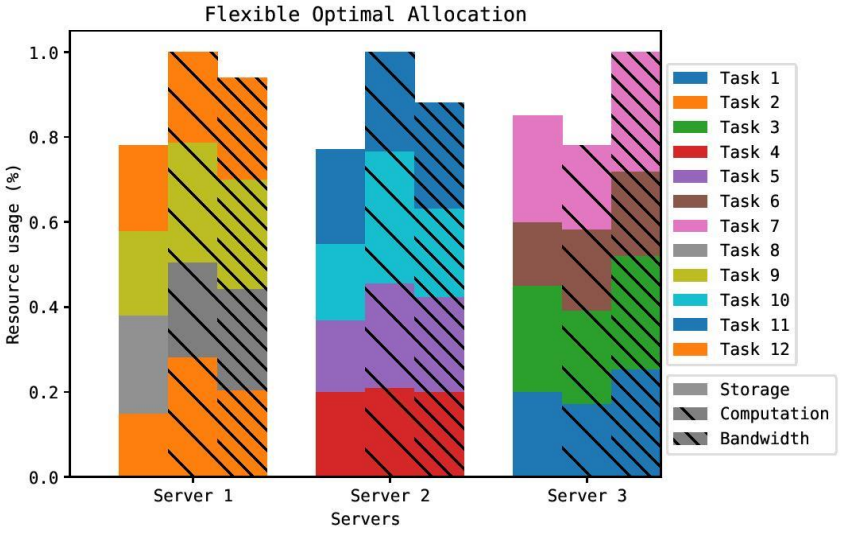
Motivation

- Edge cloud computing allows coalitions to run computationally demanding analytical tasks in military tactical networks that couldn't be run locally by the user.
- However, edge cloud computing servers have significantly fewer resources than traditional cloud computing servers.
- They therefore require efficient and effective allocation of these resources to maximise the number of tasks that can be run concurrently
- Previous research considered a fixed allocation scheme where task requested a fixed resource usage
- However, resource bottleneck can easy occur when numerous users over request particular resources, limit the number of tasks that can be run



- Here servers are described with three resources (storage, computation and bandwidth).
- Each task uses a percentage of these resources in order to run being the coloured bars.

Flexible resource allocation mechanism



- Principle – That the time taken for an operation to complete is proportional to the amount of resources allocated
- Instead task submit their resource requirement over their lifetime and a deadline to be computed by
- This is used by servers to determine how resources are allocated to individual tasks
- Algorithm aims is to maximise the social welfare (sum of task values' that are computed within the deadline)
- This proposes research challenges as no previous algorithms exist that are compatible with this mechanism and to deal with self-interested task owners who may wish to misreport their task values and requested resources.

Deadline Constraint

$$\frac{s_j}{s_j'} + \frac{w_j}{w_j'} + \frac{r_j}{r_j'} \leq d_j$$

s_j	Required Storage	s_j'	Loading task speed
w_j	Required computation	s_j'	Compute speed
r_j	Required results data	r_j'	Sending results speed
d_j	Deadline		

Optimisation problem

$$\max \sum_{\forall j \in J} v_j \left(\sum_{\forall i \in I} x_{i,j} \right) \quad (1)$$

s.t.

$$\sum_{\forall j \in J} s_j x_{i,j} \leq S_i, \quad \forall i \in I, \quad (2)$$

$$\sum_{\forall j \in J} w_j' x_{i,j} \leq W_i, \quad \forall i \in I, \quad (3)$$

$$\sum_{\forall j \in J} (r_j' + s_j') \cdot x_{i,j} \leq R_i, \quad \forall i \in I, \quad (4)$$

$$\frac{s_j}{s_j'} + \frac{w_j}{w_j'} + \frac{r_j}{r_j'} \leq d_j, \quad \forall j \in J, \quad (5)$$

$$0 \leq s_j' \leq \infty, \quad \forall j \in J, \quad (6)$$

$$0 \leq w_j' \leq \infty, \quad \forall j \in J, \quad (7)$$

$$0 \leq r_j' \leq \infty, \quad \forall j \in J, \quad (8)$$

$$\sum_{\forall i \in I} x_{i,j} \leq 1, \quad \forall j \in J, \quad (9)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J. \quad (10)$$

- Using this flexibility principle, an optimisation problem can be mathematically described
- The aim is to maximise the sum of task value that can be computed within the task deadline (equation 1)
- Constraints 2-4 limit the resource usage to be within server capacity
- Constraint 5 forces the task to be completed within its deadline
- Constraints 6-8 force the resource speeds to be positive
- Constraints 9-10 limit a task be allocated to only a single server
- This problem is NP-Hard due to being a knapsack problem

s_j	Required Storage for task j	s_j'	Loading task speed for task j
w_j	Required computation for task j	s_j'	Compute speed for task j
r_j	Required results data for task j	r_j'	Sending results speed for task j
d_j	Deadline for task j	v_j	Value of task j
S_i	Storage capacity of server i	W_i	Computational capacity of server i
R_i	Bandwidth capacity of server i	$X_{i,j}$	Allocation of task j to server i

Approaches

Properties	Greedy mechanism	Critical value auction	Decentralised Iterative auction
Strategyproof	No	Yes	No
Optimal	No	No	No (however this does occur a majority of the time)
Scalability	High	High	Medium
Information requirements from users	All information	All information	All information except the reserved private value
Communications overhead	Low	Low	High
Decentralisation	No	No	Yes

Greedy mechanism

- The algorithm has a lower-bound of 1/n of the optimal welfare. This is as it unknown after the first task is allocated if any subsequent tasks can be allocated. However in practice, this case almost never occurs.
- Algorithm steps:
    1. The list of tasks are sorted in descending order by a value density function.
    2. For each task in the sorted list, a server is selected from the list of available servers using the server selection function.
    3. Then the resource allocated is determined by a resource allocation function for the task on the server
- As a results, the algorithm has polynomial time complexity
- The algorithm however assumes that tasks are not lying about their attributes like value or required resources. This problem is addressed by the critical value auction.

Algorithm 1 Greedy Mechanism

Require: J is the set of tasks and I is the set of servers
Require: $S_i^{'}$, $W_i^{'}$ and $R_i^{'}$ is the available resources (storage, compu
tation and bandwidth respectively) for server i.
Require: $\alpha(j)$ is the value density function of a task
Require: $\beta(j, I)$ is the server selection function of a task and se
of servers returning the best server, or $\emptyset$ if the task is not able t
be run on any server
Require: $\gamma(j, i)$ is the resource allocation function of a task an
server returning the loading, compute and sending speeds
Require: $sort(X, f)$ is a function that returns a sorted list of e
ements in descending order, based on a set of elements and
function for comparing elements

$J^{'} \leftarrow sort(J, \alpha)$
for all $j \in J^{'}$ **do**
  $i \leftarrow \beta(j, I)$
  if $i \neq \emptyset$ **then**
    $s_j^{'}, w_j^{'}, r_j^{'} \leftarrow \gamma(j, i)$
    $x_{i,j} \leftarrow 1$
  end if
end for

Critical value auction

- Single parameter domain auctions are a well-researched area in mechanism design, with the critical value being the minimum value a buyer must report such that the item is still sold to them.
- Using the critical value, strategyproof (weakly-dominant incentive compatible) auctions can be created using the greedy mechanism previously explained as the method of calculating each task's critical value.
- Auction steps:
    1. The greedy mechanism is run with the reported task values to find the task that would be allocated
    2. For each task that would be allocated, we find the critical value for the task, the user then pays this value instead of the reported value as in the greedy mechanism. The critical value is found by:
        a. Removing the task from the list of sorted tasks (greedy mechanism step 1)
        b. Running the greedy mechanism normally except after each task is allocated checking if the task can still be allocated on any server
        c. Once the task is unable to be allocated to any server, the critical value density is equal to the value density of last task allocated
        d. The critical value is equal to the inverse of the value density function using the critical value density
- Due to the use of the greedy mechanism, the auction inherits the same social welfare performance as the greedy mechanism
- The auction's time complexity is still polynomial as well, as it just computes the greedy mechanism multiple times, up to number of tasks + 1.
- While any value density function can be used, in order for the auction to be strategyproof, the value density function used must be monotonic meaning that if the user misreports a task attribute, the value density must decrease.

$$\frac{v_j d_j}{s_j + w_j + r_j}$$

Decentralised iterative auction

- While the critical value auction is incentive compatible, it requires the revelation of a task's value.
- However, for some users, e.g., in tactical networks, they may not wish to reveal this information to other coalition partners.
- The VCG mechanism works by calculating the price of an auction item by finding the difference in social welfare when the task exists and doesn't exist
- We modify this mechanism to be decentralised instead of centralised such that each server calculates the difference. To do this requires a modified optimisation problem for the server to maximise task prices instead of task values.
- Auction steps:
    1. Unallocated tasks is equal to a initial list of tasks
    2. While unallocated tasks has tasks
        A. Select a random task from the list of unallocated tasks
        B. The task price is the minimum price from all of the servers which calculates its price using the modified optimisation problem
        C. If the task price is greater than the minimum price then the task is disregard otherwise allocate the task to the server
        D. However by allocated the task to the server, other tasks may be kicked off. These task are added back to the unallocated tasks list

Algorithm 2 Decentralised Iterative Auction

Require: I is the set of servers
Require: J is the set of unallocated tasks, which initial is the set of all tasks to be allocated
Require: $P(i,k)$ is solution to the problem in section 4.3.1 using the server i and new task k. The server's current tasks is known to itself and its current revenue from tasks so not passed as arguments.
Require: $R(i,k)$ is a function returning the list of tasks not able to run if task k is allocated to server i
Require: $\leftarrow_R$ will randomly select an element from a set

```
while |J| > 0 do
    j ←_R J
    p, i ← argmin_{i∈I} P(i, j)
    if p ≤ v_j then
        p_j ← p
        x_{i,j} ← 1
        for all j' ∈ R(i, j) do
            x_{i,j'} ← 0
            p'_j ← 0
            J ← J ∪ j'
        end for
    end if
    J ← J \ {j}
end while
```

Modified server optimisation problem

- A task's price is equal to the difference in the server revenue (the task doesn't exist) to when the task is included with a price of zero (plus a small value)
- This modifications to the general optimisation problem is that it is only for single server with the new task referred to as n'.
- The resulting constraints are extremely similar except that the new task is forced to be allocated to the server.
  - Objective function is to maximise the sum of computed task prices (Equation 11)
  - Constraints 12-14 limit the resource usage to be within server capacity
  - Constraint 15 forces the task to be completed within its deadline including the new task.
  - Constraints 16-18 force the resource allocation to be positive for all tasks
  - Constraints 19 limits task allocation to be binary

$$\max \sum_{\forall n \in N} p_n x_n \tag{11}$$

s.t.

$$\sum_{\forall n \in N} s_n x_n + s_{n'} \leq S_m, \tag{12}$$

$$\sum_{\forall n \in N} w_n^{'} x_n + w_{n'} \leq W_m, \tag{13}$$

$$\sum_{\forall n \in N} (r_n^{'} + s_n^{'}) \cdot x_n + (r_{n'}^{'} + s_{n'}^{'}) \leq R_m, \tag{14}$$

$$\frac{s_n}{s_n^{'}} + \frac{w_n}{w_n^{'}} + \frac{r_n}{r_n^{'}} \leq d_n, \qquad \forall n \in N \cup \{n^{'}\} \tag{15}$$

$$0 < s_n^{'} < \infty, \qquad \forall n \in N \cup \{n^{'}\} \tag{16}$$

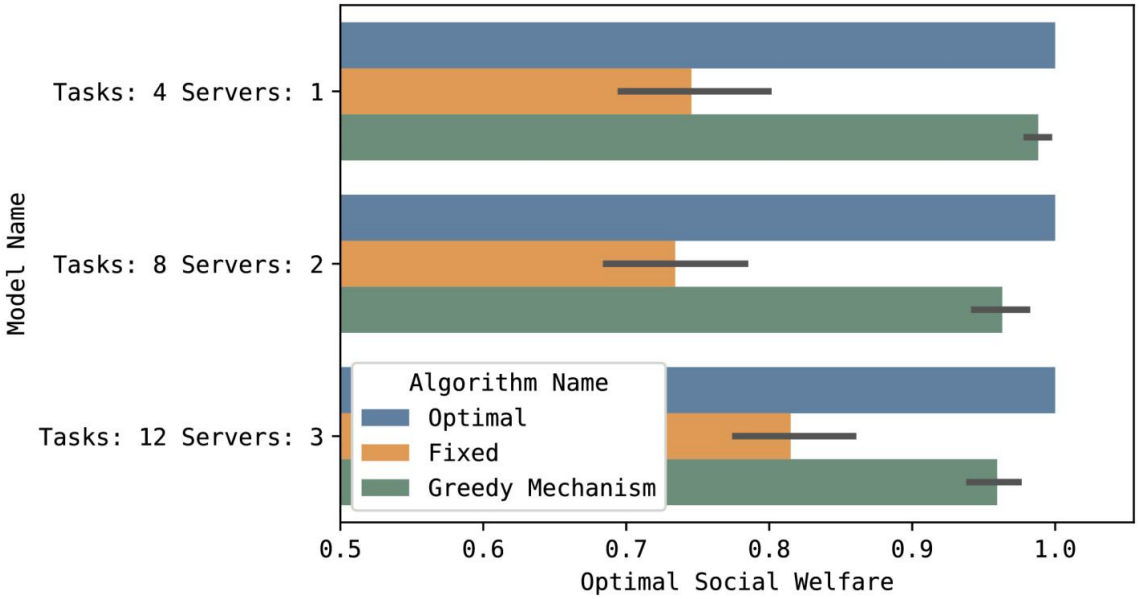
$$0 < w_n^{'} < \infty, \qquad \forall n \in N \cup \{n^{'}\} \tag{17}$$

$$0 < r_n^{'} < \infty, \qquad \forall n \in N \cup \{n^{'}\} \tag{18}$$

$$x_n \in \{0, 1\} \qquad \forall n \in N \tag{19}$$

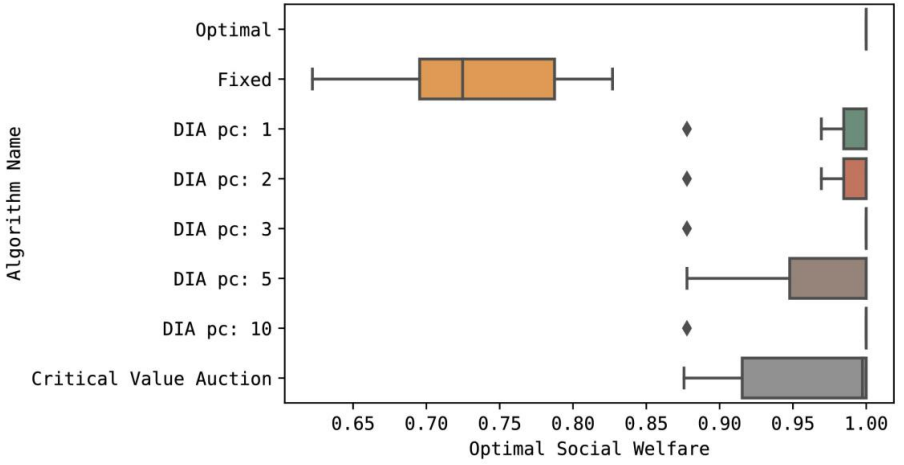
Greedy mechanism and critical value auction results

- To compare our algorithm, we implemented a time-limited optimal solver and a fixed resource allocation mechanism where the task resource usage is fixed between the server preventing any flexibility.
- These results compare the proportion of the optimal social welfare (sum of the computed task values).
- We compared results over a range of environments with different levels of supply and demand.
- With environment that have extremely high demand over a single resources, our system is extremely advantageous as it can deal with this type of pressure that normally is not possible. In cases where server resources are well distributed then this mechanism achieves similar results as the fixed version.



Decentralised Iterative auction

- The VCG auction is an economically efficient auction that finds the optimal allocation to calculate prices. We therefore use the VCG for the optimal flexible and fixed results.
- We found that a majority of the time, the DIA achieves the optimal social welfare however sometimes falls into a local optima
- We also found that the value of the price change doesn't effect the social welfare of the solution much.



Conclusion and future work

- In this work, we have presented a novel resource allocation optimisation problem along with a greedy mechanism to maximise social welfare. Along with two auction mechanisms: critical value auction for strategyproof auctions and a novel decentralised iterative auctions for users who don't wish to reveal their private task value.
- Future work is to consider an online case of this work as tasks arrive over time instead resources being allocated in batches.

Appendix B: Project management

This is the progress report submitted on the 10th of December 2019.

UNIVERSITY OF SOUTHAMPTON

Faculty of Physical Engineering and Science
School of Electronics and Computer Science

A project report submitted for the award of
MEng Electronic Engineering

Supervisor: Dr Tim Norman

Auctions for online elastic resource allocation in cloud computing

by **Mark Towers**

March 21, 2020

University of Southampton

Abstract

Faculty of Physical Engineering and Science
School of Electronics and Computer Science

A project report submitted for the award of MEng Electronic Engineering

Auctions for online elastic resource allocation in cloud computing

by Mark Towers

Edge clouds enable computational tasks to be completed at the edge of the network, without relying on access to remote data centres. A key challenge in these settings is that limited computational resources often need to be allocated to many self-interested users. Here, existing resource allocation approaches usually assume that tasks have inelastic resource requirements (i.e., a fixed amount of compute time, bandwidth and storage), which may result in inefficient resource use. In this paper, we expand previous work to an online setting such that job will arrive over time with the task prices and resource allocation determined through training an agent using reinforcement learning.

Contents

Declaration of Authorship

I declare that this thesis and the work presented in it is my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a degree at this University;
2. Where any part of this thesis has previously been submitted for any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as: S.R. Gunn. Pdflatex instructions, 2001. URL http://www.ecs.soton.ac.uk/~srg/softwaretools/document/
   C. J. Lovell. Updated templates, 2011
   S.R. Gunn and C. J. Lovell. Updated templates reference 2, 2011

Signed:..... Date:.....

Acknowledgements

This project wouldn't have started without Dr Sebastian Stein and a team of Pennsylvania State University that has produced a paper investigating the static case of this problem. So I am grateful for the support they gave in kick starting this project.

My housemates for surviving with me pestering them about proof reading my paper and this project, all of the time.

Chapter 1

Introduction

Google Cloud Platform, Amazon Web Service and Microsoft Azure provide a service to users with computer programs that are too large, difficult or time consuming to be run on standard computer. User can request a fixed amount of resources to run the program, e.g. cpu cores, RAM, hard drive space, bandwidth, etc. However, this can create bottlenecks on certain resources due to large numbers of resource requests preventing other jobs from running. This problem is particularly relevant in edge cloud computing as servers are small thus making the demand on resources much greater. This project considers the case where the user states the total resource requirements for the program instead of the standard procedure that user request a fixed amount of resources. This allows the cloud provider the ability to balance resource demand as it has complete knowledge of all user's requirements and can flexibly change the amount of resources allocated to each task. This can prevent bottlenecks through proper balances of resources allowing more tasks to run simultaneously and can also lower the price due to there being a lower overall demand on resources.

Recently, cloud computing (Bahrami , 2015) has become a popular solution for remotely running data-intensive applications. But for some problem domains, it is not possible to use large cloud providers, for example running highly delay-sensitive tasks or where connectivity to the cloud is intermittent. Mobile edge computing (Mao et al., 2017) has emerged as a complementary paradigm to allow for small data-centers, close to users, to execute tasks. These data centers are known as edge clouds.

Disaster response, smart cities and Internet-of-things (IoT) are popular technologies that utilise mobile edge computing due to the use of ability to process

small programs locally with low latency. For smart cities, this allows for the possibly of smart intersections with the use of road-side sensors or smart traffic lights based on cameras to minimise the waiting times (Mustapha et al., 2018). Or for the police to analysis CCTV footage to spot suspicious behaviour or to track people between cameras (Sreenu and Saleem Durai, 2019). In the case of disaster response, maps can be produced using autonomous vehicles sensors to be used in the search for potential victims and support responders (Alazawi et al., 2014).

To compute these task, several types of resources are required included communication bandwidth, computational power and data storage resources (Farhadi et al., 2019). Tasks will have a deadline such that the program must be completed before this point and a private value. This value is depend on the program itself and its value to the owner, .e.g analysis air pollution is less important than preventing traffic jams at rush hour or tracking a criminal on the run. This project is interested in allocated task to servers to maximise the social welfare (sum of all allocated task values) over time. But due to users being self-interested, they may behave strategically (Bi et al., 2019) or prefer to not reveal their value publicity (Pai and Roth, 2013).

The shortcoming of existing work for resource allocation in edge cloud computing (Farhadi et al., 2019; Bi et al., 2019) has the assumption that tasks have fixed resource requirements. However, flexibility is possible in practise with how resources are allocaed to each task. For example, the allocated bandwidth for loading the program is proportional to the time taken to load the program. This is true of also the computational requirements and for sending results back to the user. This project investigates flexible allocation of resource and pricing mechanisms when task arrive over time and have private values.

Chapter 2

Related Works

Due to the novel approach for resource allocation in cloud computing, there is few papers that allow for flexible resource allocation. However there is a considerable amount of research in the area of resource allocation and pricing in cloud computing, some of which use auction mechanisms to deal with competition Kumar et al. (2017); Zhang et al. (2017); Bingqian Du (2019); Bi et al. (2019). In Section 2.1 considers the previously related work for flexible resource allocation in cloud computing and Section 2.2 consider recent work in the field of reinforcement learning.

2.1 Related work in Cloud computing

A majority of the approaches for pricing and resource allocation in cloud computing require users to request a fixed amount of certain resource with the cloud provider having no control over the resources only the servers that the task was allocated to (Kumar et al., 2017; Zhang et al., 2017; Bingqian Du, 2019; Bi et al., 2019). The flexible approach that this project assumed has only been considered in Towers et al. that allows the server to distribute its resources more efficiently based on each task's requirements. The primary difference between this project and that paper is that this project considers the addition of time allowing for resource speed to change over time and that there are task stages.

Previous work by Towers et al. considers three solutions to a single-shot problem case, a greedy algorithm to quickly approximate a solution to maximise the social welfare and two auction mechanisms as server are normally paid

for usage of their resources. The greedy algorithm is a polynomial time algorithm that will find solution within $\frac{1}{n}$ of the optimal social welfare. This is done through the use of modular heuristics for ordering the task by density then for each task, select a server based on available resource on each servers then to allocate resources that minimises a resource heuristics. Using certain heuristics, the greedy algorithm achieves at least 90% of the optimal solution and 20% more than optimal solution for fixed resource equivalent problems. A new distributed iterative auction was developed that use a reverse vcg principle to calculate a task price that meant that a task didnt need to reveal its private value also that the auction could be run in a decentralised way. This means that the auction is budget balanced however it is not economically efficient or incentive compatible. The third algorithm is an implementation of a single parameter auctions (Nisan et al., 2007) using the greedy algorithm to find the critical value of a task. Using this mechanism with a monotonic value density heuristic means that the auction is incentive compatible.

Other closely related work on resource allocation in edge clouds Farhadi et al. (2019) considers both the placement of code/data needed to run a specific task, as well as the scheduling of tasks to different edge clouds. The goal there is to maximize the expected rate of successfully accomplished tasks over time. Our work is different both in the setup and the objective function. Our objective is to maximize the value over all tasks. In terms of the setup, they assume that data/code can be shared and they do not consider the elasticity of resources.

2.2 Related work in Reinforcement learning

Supervised learning allows for the training of agents to converge towards a truth value while unsupervised learning allows for the training of agents find pattern for data where no-truth value exist. Reinforcement learning works in the middle ground where truth value exist but are unknown so agent will interact with an environment that depending on certain actions will result in being rewarded. Using this resulted in the first successful ”machine-learning” agent in 1959 with TD-Checking (Samuel, 1988) where the truth value was the difference in two ”neighbouring” checkers boards. Temporal difference, Q-learning, SARSA and other were early training methods for agents using reinforcement learning.

The work of Mnih et al. (2013) developed the usage of these methods much further by coupling them with deep neural network allowing an agent to be trained using the same algorithm to achieve state-of-the-art in 6 of 7 games tried and superhuman scores in 3. This recent work has reinvigorated to the area primarily due to the availability of data to be used and the computational power available. This has allowed Silver et al. (2017) to achieve mastery of the game of Go learning from no human expert to beat the world champion 4 games to 1. With following work expanding to other games like DOTA 2 (OpenAI) beating the world champions and Starcraft 2 (Vinyals et al., 2017) becoming in the top 2% world wide.

Chapter 3

Proposed solution

The problem case presented in Chapter 1 has two stages: auction and resource allocation. These stages are discussed in sections 3.2 and 3.3 respectively.

3.1 Optimisation problem

A sketch of the system is shown in Fig. 3.1. We assume that in the system there is a set of $I = \{1, 2, \ldots, |I|\}$ servers are heterogeneous in all characters. Each server has a fixed availability of resources: storage for the code/data needed to run a task (e.g., measured in GB), computation capacity in terms of CPU cycles per time interval (e.g., measured in FLOP/s), and communication bandwidth to receive the data and to send back the results of the task after execution (e.g., measured in Mbit/s). We denote these resources for server i: the storage capacity as S_i, computation capacity as W_i, and the communication capacity as R_i.

There is a set $J = \{1, 2, \ldots, |J|\}$ of different tasks that require service from one of the servers in set $I = \{1, 2, \ldots, |I|\}$. To run any of these tasks on a server requires storing the appropriate code/data on the same server. These could be, for example, a set of images, videos or CNN layers in identification tasks. The storage size of task j is denoted as s_j with the rate at which the program is transferred to the server i at time t being $s'_{i,j,t}$. For a task to be computed successfully, it must fetch and execute instructions on a CPU. We consider the total number of CPU cycles required for the program to be w_j, where the rate at which the CPU cycles are assigned to the task on server i at time t is $w'_{i,j,t}$. Finally, after

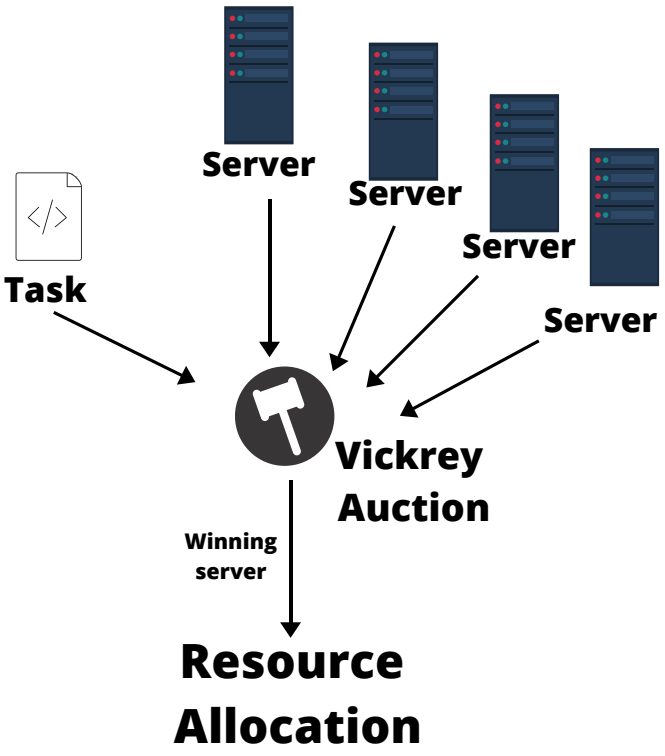


FIGURE 3.1: System model

the task is run and the results obtained, the latter need to be sent back to the user. The size of the results for task j is denoted with r_j, and the rate at which they are sent back to the user is $r'_{i,j,t}$ on server i at time t. Every task has a beginning time, denoted by b_j and a deadline, denoted by d_j. This is the maximum time for the task to be completed in order for the user to derive its value. This time includes: the time required to send the data/code to the server, run it on the server, and get back the results. Therefore for the task to be successfully completed, it must completed fulfill the constraint in equation (3.1). These operations must occur in order (loading, computing then sending of results) as a server couldn't compute a task that was not fully loaded on the machine.

$$\frac{s_j}{\sum_{t=b_j}^{d_j} s'_{i,j,t}} + \frac{w_j}{\sum_{t=b_j}^{d_j} w'_{i,j,t}} + \frac{r_j}{\sum_{t=b_j}^{d_j} r'_{i,j,t}} \leq d_j \qquad \forall j \in J \qquad (3.1)$$

As server have limited capacity, the total resource usages for all tasks running on a server must be capped. The storage constraint (equation (3.2)) is unique as the previous amount loaded in kept till the end of a program on server. While

the computation capacity (equation (3.3) is the sum of compute used by all of the tasks on a server i at time t and the bandwidth capacity (equation (3.4)) is the sum of loading and sending usages by tasks.

$$\sum_{j \in J} \left(\sum_{t=b_j}^{d_j} s'_{i,j,t} \right) \leq S_i, \qquad \forall i \in I \tag{3.2}$$

$$\sum_{j \in J} w'_{i,j,t} \leq W_i, \qquad \forall i \in I, t \in T \tag{3.3}$$

$$\sum_{j \in J} s'_{i,j,t} + r'_{i,j,t} \leq R_i, \qquad \forall i \in I, t \in T \tag{3.4}$$

$$\tag{3.5}$$

3.2 Auction solution

If an agent wish to run on task on the cloud, the task can be put forward with its requirements of required storage, computation, results data and deadline. In order for fast and truthful, a reverse Vickrey auction (Vickrey, 1961) will be implemented where servers all submit their bid for the task with the winner being the server with the lowest price but actually only gains second lowest price. The Vickrey auction is incentive compatible meaning that the dominant strategy for bidding on a task is to bid your truthful value for a task. This should help server as they dont need to learn how to outbid another agent as it only needs to consider its own evaluation. As there is also only a single round of bidding compared to alternative auctions like English or Dutch auctions, this makes auctioning fast no matter the number of servers and it also allows for a reserve price to be used.

In order to calculate the price of the task for a server requires a understanding the resource requirements of the task, the future supply and demand for tasks and the resource requirements of currently allocated tasks. Due to the complexity in creating a heuristic that can accurately use this information and the amount of memory required for a table based approach. Because of this, a long/short term memory (LSTM) will be implemented (Hochreiter and Schmidhuber, 1997) for evaluating the price of a task. The justified for the use of this network over other neural network models is explained in Section 4.1. The network would take as input, the currently allocated tasks requirements, the

possible task requirements and the server resource capacity, outputting just a single value representing the price of the task, normalised between 0 and 100.

3.3 Resource allocation solution

In previous work (Towers et al.), that utilised a single shot problem case where jobs wouldnt arrive over time, the resource speeds set were fixed and assumed that a task loading, computing and sending result occurred concurrently. With the addition of time, results in these assumptions not to hold anymore as tasks contain stages for the loading, computing and sending of results thus requiring allocated resource speeds to change over time. Therefore at each time step, a server needs to reallocate all of its resource to its currently allocated tasks as some tasks will have completely one of its stages.

In order to select how to allocate resource to tasks, this problem doesn't seem as complex as the pricing in section 3.2 therefore simple heuristic and long/short term memory neural network will be implemented and compared. This is justified in section 4.2. The LSTM will take as input, all of the currently allocated tasks that are at a particular stages resource requirements and the task's resource requirement returning a single value between 1 to 100. Once this is completed for each job, the percentage of the total values will be assigned to each task.

3.4 Training and reward schemes

There are three popular types of training methods for neural networks: supervised, unsupervised and reinforcement learning. This project will utilise reinforcement learning as supervised learning requires truth labels for data that for this problem case is too difficult to compute. While Unsupervised learning is generally used for grouping data together in groups making it not appropriate for this project. Therefore reinforcement learning will be utilised as the agent will interact with the environment resulting in actions and can earn rewards through certain actions.

The reward scheme for the pricing heuristic is equivalent to the winning bid however if the task fails to be completed then the negative bid is the reward

given at the time the task at auction. This aims to force the heuristic to only bid on tasks that it can complete but not to penalise if the agent fails to win a task in an auction. The agent's future discount variable will stop after the deadline of the task as the reward of the agent winning a task has the largest affect now and it affects shouldn't continue when the task is not allocated.

Resource allocation uses a reward scheme similar to the pricing heuristics except that the reward will be awarded at the point that the task is completed. If the task fails to complete then the reward is negative of the task price and the agent's future discount variable is also similar pricing reward scheme.

Chapter 4

Justification of the approach

The proposed solution in Chapter 3 as two parts explained in section 3.2 and 3.3. This chapter explains the reason for why each section is being solved in its particular way.

As the approaches to pricing and resource allocation heuristics are using neural networks to find the optimal function, table 4.1 has a description of how the networks architectures differ.

Neural Network	**Description**
Artificial neural networks (ANN) McCulloch and Pitts (1943)	Originally developed as a theoretically approximation for the brain, it was found that for networks with at least one hidden layer that a neural network could approximate any function (Csáji, 2001). This made neural networks extremely helpful for cases where a function would normally to difficult to find the exact function, an ANN could be trained through supervised learning to be a close approximation to the true function.
Recurrent neural network (RNN) Elman (1990)	A major weakness of ANN's is that it must use a fixed input and output making it unusable with text, sound or video where the previous data in important in understanding an input. RNN's extend ANN's to allow for connections to neurons again so that the network is not stateless compared to ANN. This means that individual letters of a words can be passed in with the network "remembering" the previous letter.

Long/Short Term Memory (LSTM) Hochreiter and Schmidhuber (1997)	While RNN's can "remember" previous inputs to the network, it also struggles from the vanishing or exploding gradient problem where gradient tends to zero or infinity making it unuseable. LSTM aims to prevent this by using forget gates that determines how much information the next state will get, allowing for more complexity information to be learnt compared to RNN's
Gated Recurrent unit (GRU) Chung et al. (2014)	GRU are very similar to LSTM, except that they use different wiring and a single less gate, using an update gate instead of a forgot gate. These additional mean that the they run faster and are easier to code than LSTM however are not as expressive allowing for less complex functions to be encoded.
Neural Turing Machine (NTM) Graves et al. (2014)	Inspired by computers, neural turing machines build on LSTM by using an external memory module that instead of memory being inbuild in a neuron. This allows for external observers to understand what is going on much better than LSTM due to its black-box nature.
Differentiable neural computer (DNC) Graves et al. (2016)	An expansion to the NTM where the memory module is scalable in size allowing for additional memory to be added if needed.

TABLE 4.1: Neural network descriptions

4.1 Justification for the auction

The auction stage (discussed in Section 3.2) has two considerations, the auction type and the pricing method.

In auction theory, there are numerous types of auctions that have different properties and uses in different areas. The area in which this project is interested in is single indivisible items as while the item has multiple resource requires, a server is required to buy the task as a single unit. Table 4.2 outlines a description of possible auctions while table 4.3 outline the most important properties that an auction has.

Auction type	Description
English auction	A traditional auction where all participant can bid on a single item with the price slowing ascending till only a single participant is left who pays the final bid price. Due to the number of rounds, this requires a large amount of communication and requires tasks to be auctioned in series.
Dutch auction	The reverse of the English auction where the starting price is higher than anyone is willing to pay with the price slowly dropping till the first participant ”jumps in”. This can result in sub-optimal pricing if the starting price is not highest enough and the latency can have a large effect on the winner.
Japanese auction	Similar to the English auction except that the auction occurs over a set period of time with the last highest bid being the winner. This means that it has the same disadvantages as the English auction except that there is no guarantee that the price will converge to the maximum. Plus additional factors like latency can have a large effect on the winner that will have a larger affect in the application of this project, edge cloud computing. But this time limit results in the auction taking a fixed amount of time unlike the English or Dutch auctions.
Blind auction	Also known as a First-price sealed-bid auction, all participants submit a single secret bid for an item with the highest bid winning and pays their bid value. As a result there is no dominant strategy (not incentive compatible) as an agent would not wish to bid higher than their task evaluation but if all other agents bid significantly lower then it would have been beneficial for the agent to bid much lower than their true evaluation. Due there being a single round of biding, latency doesn't affect an agent and many more auctions could occur within the same time a English, Dutch or Japanese auction would take to run.

Vickrey auction (Vickrey, 1961)	Also known as a second-price sealed bid auction, all participants submit a single secret bid for an item with the highest bid winning but it only pays the price of the second highest bid. Because of this, it is a dominant strategy for an agent to bid its true value as even if the bid is much higher than all other participants its doesn't matter.

TABLE 4.2: Descriptions of auctions

Auction	Incentive compatible	Iterative	Fixed time length
English	False	True	False
Japanese	False	True	True
Dutch	False	True	False
Blind	False	False	True
Vickrey	True	False	True

TABLE 4.3: Properties of the auctions described in Table 4.2

Due to the properties of the Vickrey auction (table 4.3), I believe that it is the best auction to be used. The greatest advantage of the auction is that it is strategyproof meaning the dominant strategy is to truthful bid its price. This means that agents don't have to learn a strategy as with the blind auction where the agent must learn to bid only just lower than other agents. Another advantage of the auction is that it is not iterative, making the auction fast with only a single round and can give a fixed time limit from the task being published to all server bids to be submitted.

However, the standard Vickrey auction will not be used as the task is buying the resources from a server not a server buying the task. But due to resource allocation, the server must bid on the task so the Vickrey auction implemented will work in reverse so the lowest bid will win and the task must pay the second-lowest bid. In the final report, a proof will be provided to show that a reverse Vickrey auction is still incentive compatible.

The second part of the auction solution is the pricing heuristic. I believe that the pricing heuristic would be too complex to encoded into an algorithm if by hand due its need to understand: future resource allocation of currently allocated jobs and the resource requirements of the task. Therefore due to neural network being able to approximate any function (Csáji, 2001) and reinforcement learning

methods to training without truth data (Section 2.2). I have outlined in Table 4.1 the properties of popular neural network architectures that would allow for a variable amount of inputs (except for ANN). This is due to having to input to the network the currently allocated tasks to a server that till compute time is of unknown length. Of the available architecture, I predict the Long/Short term memory model is the simplest model that will require the least training but still with the complexity to encode the heuristic. With the Neural Turing Machine and Differentiable Neural Network, these networks are extremely complex and require a large amount of data to train the networks. Also the ability of these networks to be able to store data in external storage is not important as the data doesn't need to be store for future inputs. The opposite problem exists for the Recurrent neural network or the Gated Recurrent unit that they are possibly not complex enough for the pricing heuristic.

4.2 Justification for resource allocation

The justification for the resource allocation neural network choice is very similar justification to the previous section (section 4.1). Long/short term memory architecture should be complex enough for the resource allocation but it is possible that the abilily to use external storage of Neural Turing machine and Differentiable Neural network to store the allocation of resource to previous tasks. But I don't believe that this additional complexity will allow for the heuristic to do later better but it could be investigated in future work.

The reason that the output of the neural network is normalised is done as it would require the network to learn less compared to if the network has output the amount of the available resources for a task. Whereas in a normalised value, the network can output how ”important” allocation of resources are for a task not the exact amount of resources allocated.

Chapter 5

Work requirements

For the project, the additional support I will require is more compute power for training of the neural networks. Because of this, I will request access to Iridis 4 with GPUs.

5.1 Work to date

As this project is an extension to previous work done in the Agent, Interaction and Complexity research labs that has produced the paper in Section 5.2. The majority of this research occurred over the summer of 2019 with the paper that is currently under peer review done from October 2019 to 15th November 2019. The paper produced was done with support from Dr Fidan Mehmeti and Dr Sebastian Stein with myself being the primary author.

For the remaining time, I have studied reinforcement learning that is the primary technological additional that will be used in the proposed solution (section 3) and described in Section 2.2.

5.2 Plan of the remaining work

Due to this term having been completing the paper (Section 5.2), I have not done any programming towards the project. Therefore the begin of the next term will be spend building the framework for which different pricing and resource allocation heuristics can be applied and compared. Once this has been

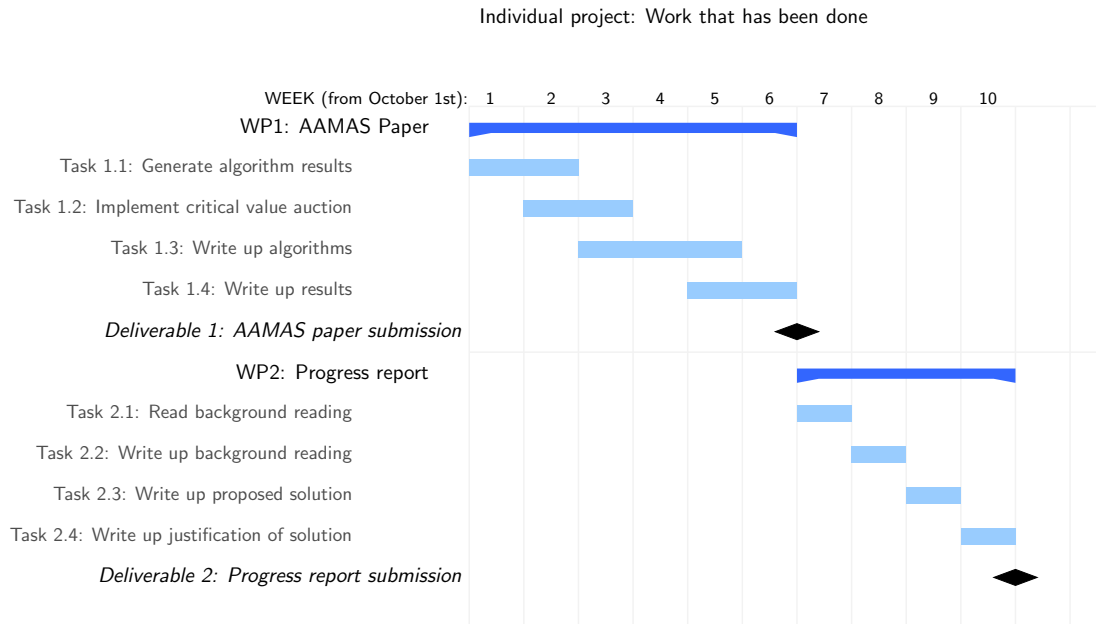


FIGURE 5.1: Work that has been done to date

completed, analysis and comparison of the heuristic will be done with different server and task models. Resulting in a final paper.

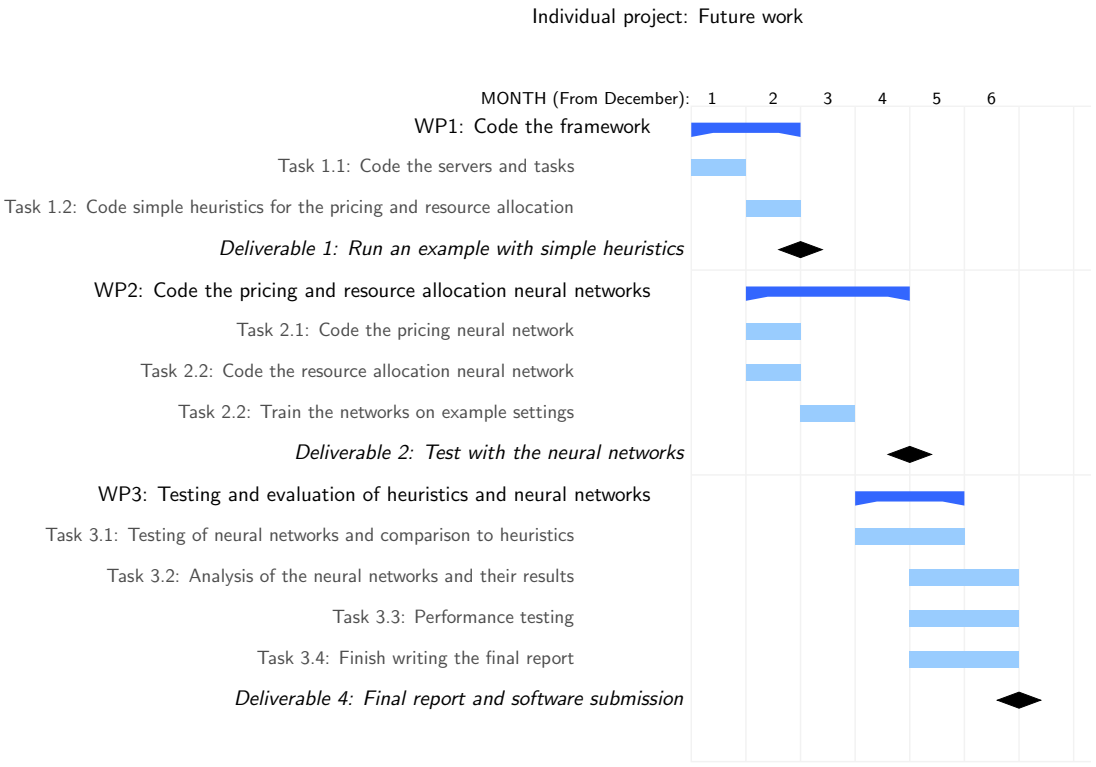


FIGURE 5.2: Work that will be done in the future

Appendices

Appendix A: Paper

This paper has been submitted to the International Conference on Autonomous Agents and Multiagent Systems (AAMAS) 2020 at the University of Auckland. The paper is under peer-review with the authors being myself, Sebastian Stein, Tim Norman, Fidan Mehmeti, Tom La Porta, Caroline Rubein and Geeth Demel and within this project is referred to as Towers et al.. A copy of the paper is found below.

Auction-based Mechanisms for Allocating Elastic Resources in Edge Clouds

Paper #1263

ABSTRACT

Edge clouds enable computational tasks to be completed at the edge of the network, without relying on access to remote data centres. A key challenge in these settings is that limited computational resources often need to be allocated to many self-interested users. Here, existing resource allocation approaches usually assume that tasks have inelastic resource requirements (i.e., a fixed amount of compute time, bandwidth and storage), which may result in inefficient resource use. To address this, we propose a novel approach that takes advantage of the elastic nature of some of the resources, e.g., to trade off computation speed with bandwidth if this allows a server to execute more tasks by their deadlines. We describe this problem formally, show that it is NP-hard and then propose a scalable approximation algorithm. To deal with the self-interested nature of users, we show how to design a centralized auction that incentives truthful reporting of task requirements and values. Moreover, we propose novel auction-based decentralized approaches that are not always truthful, but that limit the information required from users and that can be adjusted to trade off convergence speed with solution quality. In extensive simulations, we show that considering the elasticity of resources leads to a gain in utility of around 20% compared to existing fixed approaches and that our novel auction-based approaches typically achieve 95% of the theoretical optimal.

KEYWORDS

Edge clouds; elastic resources; auctions

1 INTRODUCTION

In the last few years, cloud computing [2] has become a popular solution to run data-intensive applications remotely. However, in some application domains, it is not feasible to rely a remote cloud, for example when running highly delay-sensitive and computationally-intensive tasks, or when connectivity to the cloud is intermittent. To deal with such domains, *mobile edge computing* [13] has emerged as a complementary paradigm, where computational tasks are executed at the edge of mobile networks at small data-centers, known as *edge clouds*.

Mobile edge computing is a key enabling technology for the Internet-of-Things (IoT) [6] and in particular applications in smart cities [19] and disaster response scenarios [9]. In these applications, low-powered devices generate computational tasks and data that have to be processed quickly on local edge cloud servers. More specifically, in smart cities, these devices could be smart intersections that collect data from road-side sensors and vehicles to produce an efficient traffic light sequence to minimize waiting times [14]; or it could be CCTV cameras that analyse video feeds for suspicious behaviour, e.g., to detect a stabbing or other crime in progress [20]. In disaster response, sensor data from autonomous vehicles (including video, sonar and LIDAR) can be aggregated in real time to produce maps of a devastated area, search for potential victims and help first responders in focusing their efforts to save lives [1].

To accomplish these tasks, there are typically several types of resources that are needed, including communication bandwidth, computational power and data storage resources [7], and tasks are generally delay-sensitive, i.e., have a specific completion deadline. When accomplished, different tasks carry different values for their owners (e.g., the users of IoT devices or other stakeholders such as the police or traffic authority). This value will depend on the importance of the task, e.g., analysing current levels of air pollution may be less important than preventing a large-scale traffic jam at peak times or tracking a terrorist on the run. Given that edge clouds are often highly constrained in their resources [12], we are interested in allocating tasks to edge cloud servers to maximize the overall social welfare achieved (i.e., the sum of all task values). This is particularly challenging, because users in edge clouds are typically self-interested and may behave strategically [3] or may prefer not to reveal private information about their values to a central allocation mechanism [18].

An important shortcoming of existing work looking at resource allocation in edge clouds, e.g., [3, 7], is that it assumes tasks have strict resource requirements — that is, each task consumes a fixed amount of computation (CPU cycles per time), takes up a fixed amount of bandwidth to transfer data and uses up a fixed amount of storage on the server. However, in practice, edge cloud servers have some flexibility in how they allocate limited resources to each task. In more detail, to execute a task, the corresponding data and/or code first has to be transferred to the server it is assigned to, requiring some bandwidth. This then takes up storage on the server. Next, the task needs computing power from the server in terms of CPU cycles per time. Once computation is complete, the results have to be transferred back to the user, requiring further bandwidth. Now, while the the storage capacity at the server for every task is *strict*, since the task cannot be run unless all the data are stored, the bandwidth allocation and the speed at which the task is run on the server are *elastic*. The latter two depend on how tight the task's deadline is, and can be adjusted accordingly, so that more tasks can receive service simultaneously. Allocating the elastic resources optimally is the focus of this paper.

Against this background, we make the following novel contributions to the state of the art:

Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), B. An, N. Yorke-Smith, A. El Fallah Seghrouchni, G. Sukthankar (eds.), May 2020, Auckland, New Zealand

https://doi.org/doi

- We formulate an optimization problem for assigning the tasks to the servers, whose objective is to maximize total social welfare, taking into account resource limitations and allowing elastic allocation of resources.
- We prove that the problem is NP-hard and propose an approximation algorithm with a performance guarantee of $\frac{1}{n}$, where n is the number of tasks, and a linearithmic computational complexity, i.e., $O(n \log(n))$.
- We propose a range of auction-based mechanisms to deal with the self-interested nature of users. These offer various trade-offs regarding truthfulness, optimality, scalability, information requirements from users, communication overheads and decentralization.
- Using extensive realistic simulations, we compare the performance of our algorithm against other benchmark algorithms, and show that our algorithm outperforms all of them, while at the same time being within 95% to the optimal solution.

The paper is organized as follows. In the next section we discuss related work. This is followed by the problem formulation in Section 3. Our novel resource allocation mechanisms are presented in Section 4. In Section 5, we evaluate the performance of our mechanisms and compare them against the optimal solution and other benchmarks. Finally, Section 6 concludes the work.

2 RELATED WORK

There is a considerable amount of research in the area of resource allocation and pricing in cloud computing, some of which use auction mechanisms to deal with competition [3, 4, 11, 22]. However, these approaches assume that users request a fixed amount of resources system resources and processing rates, with the cloud provider having no control over the speeds, only the servers that the task was allocated to. In our work, tasks' owners report deadlines and overall data and computation requirements, allowing the edge cloud server to distribute its resources more efficiently based on each task's requirements.

Our problem is related to multidimensional knapsack problems. In particular, Nip et al. [15] consider flexibility in the allocation, with linear constraints that are used for elastic weights. The paper provides a pseudo-polynomial time complexity algorithm for solving this problem to maximize the values in the knapsack. Our problem case is similar to their problem, but our problem has non-linear constraints due to the deadline constraint, so their algorithm cannot be applied here.

Other closely related work on resource allocation in edge clouds [7] considers both the placement of code/data needed to run a specific task, as well as the scheduling of tasks to different edge clouds. The goal there is to maximize the expected rate of successfully accomplished tasks over time. Our work is different both in the setup and the objective function. Our objective is to maximize the value over all tasks. In terms of the setup, they assume that data/code can be shared and they do not consider the elasticity of resources.

3 PROBLEM FORMULATION

In this section we first describe the system model. Then, we present the optimization problem and prove its NP-hardness.

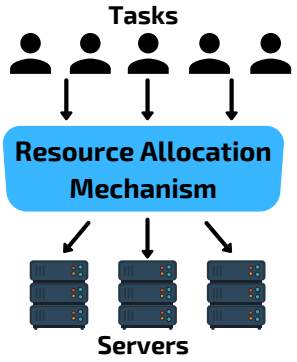


Figure 1: System Model

3.1 System model

A sketch of the system is shown in Fig. 1. We assume that in the system there is a set of servers $I = \{1, 2, \ldots, |I|\}$ servers, which could be edge clouds that can be accessed either through cellular base stations or WiFi access points (APs). Servers have different types of resources: storage for the code/data needed to run a task (e.g., measured in GB), computation capacity in terms of CPU cycles per time interval (e.g., measured in FLOP/s), and communication bandwidth to receive the data and to send back the results of the task after execution (e.g., measured in Mbit/s). We assume that the servers are heterogeneous in all their characteristics. More formally, we denote the storage capacity of server i with S_i, computation capacity with W_i, and the communication capacity with R_i.

There is a set $J = \{1, 2, \ldots, |J|\}$ of different tasks that require service from one of the servers.[1] Every task $j \in J$ has a value v_j that represents the value of running the task to its owner. To run any of these tasks on a server requires storing the appropriate code/data on the same server. These could be, for example, a set of images, videos or CNN layers in identification tasks. The storage size of task j is denoted as s_j with the rate at which the program is transferred to the server being $s_j^{'}$. For a task to be computed successfully, it must fetch and execute instructions on a CPU. We consider the total number of CPU cycles required for the program to be w_j, where the rate at which the CPU cycles are assigned to the task per unit of time is $w_j^{'}$. Finally, after the task is run and the results obtained, the latter need to be sent back to the user. The size of the results for task j is denoted with r_j, and the rate at which they are sent back to the user is $r_j^{'}$. Every task has its deadline, denoted by d_j. This is the maximum time for the task to be completed in order for the user to derive its value. This time includes: the time required to send the data/code to the server, run it on the server, and get back the results. We assume that there is an *all* or *nothing* task execution reward scheme, meaning that for the task value to be awarded the entire task must be run and the results sent back within the deadline.

[1] We focus on a single-shot setting in this paper. In practice, an allocation mechanism would repeat the allocation decisions described here over regular time intervals, with longer-running tasks re-appearing on consecutive time intervals. We leave a detailed study of this to future work.

3.2 Optimization problem

Given the aforementioned assumptions, the optimal assignment of tasks to servers and optimal allocation of resources in a server to the tasks assigned to that server is obtained as a solution to the following optimization problem. Here, the decision variables are $x_{i,j} \in \{0,1\}$ (whether to run task j on server i) as well as $s_j^{'}$, $r_j^{'}$ and $w_j^{'}$ (indicating the bandwidth rates for transferring the code, for returning the results and the CPU cycles per unit of time, respectively).

$$\max \sum_{\forall j \in J} v_j \left(\sum_{\forall i \in I} x_{i,j} \right) \tag{1}$$

s.t.

$$\sum_{\forall j \in J} s_j x_{i,j} \leq S_i, \qquad \forall i \in I, \tag{2}$$

$$\sum_{\forall j \in J} w_j^{'} x_{i,j} \leq W_i, \qquad \forall i \in I, \tag{3}$$

$$\sum_{\forall j \in J} (r_j^{'} + s_j^{'}) \cdot x_{i,j} \leq R_i, \qquad \forall i \in I, \tag{4}$$

$$\frac{s_j}{s_j^{'}} + \frac{w_j}{w_j^{'}} + \frac{r_j}{r_j^{'}} \leq d_j, \qquad \forall j \in J, \tag{5}$$

$$0 \leq s_j^{'} \leq \infty, \qquad \forall j \in J, \tag{6}$$

$$0 \leq w_j^{'} \leq \infty, \qquad \forall j \in J, \tag{7}$$

$$0 \leq r_j^{'} \leq \infty, \qquad \forall j \in J, \tag{8}$$

$$\sum_{\forall i \in I} x_{i,j} \leq 1, \qquad \forall j \in J, \tag{9}$$

$$x_{i,j} \in \{0,1\}, \qquad \forall i \in I, \forall j \in J. \tag{10}$$

The objective (Eq.(1)) is to maximize the total value over all tasks (i.e., the social welfare). Task j will receive the full value v_j only if it is executed entirely and the results are obtained within the deadline for that task. Constraint (Eq.(2)) relates to the finite storage capacity of every server to store code/data for the tasks that are to be run. The finite computation capacity of every server is expressed through Eq.(3), whereas Eq.(4) denotes the constraint on the communication capacity of the servers. As can be seen, the communication bandwidth comprises two parts: one part to send the data/code or request to the server, and the other part to get the results back to the user.[2] Constraint Eq.(5) is the deadline associated with every task, where the total time of the task in the system is the sum of the time to send the request and code/data to the server, time to run the task, and the time it takes the server to send all the results to the user. Note that if a task is not run on any server, this constraint can be satisfied by choosing arbitrarily high bandwidth and CPU rates (without being constrained by the resource limits of any server). The rates at which the code is sent, run and the results are sent back are all positive and finite (Eqs. (6), (7), (8)). Further, every task is served by at most one server (Eq.(9)). Finally, a task is either served or not (Eq.(10)).

[2]Not that sending and receiving data will not always overlap, but for tractability we assume they deplete a common limited bandwidth resource per time step. This ensures that the bandwidth constraint is always satisfied in practice.

Complexity: In the following we show that this optimization problem is NP-hard.

Theorem 3.1. *The optimization problem* (1)-(10) *is NP-hard.*

Proof. The optimization problem without constraint (5) is a 0-1 multidimensional knapsack problem [10], which is a generalization of a simple 0-1 knapsack problem. The latter is an NP-hard problem [10]. Given this, it follows that the 0-1 multidimensional knapsack problem is also NP-hard. Since optimization problem (1)-(10) is a generalization of a 0-1 multidimensional knapsack problem, it follows that it is NP-hard as well. □

Before we propose our novel allocation mechanisms for the allocation problem with elastic resources, we briefly outline an example that illustrates why considering this elasticity is important. In this example, there are 12 potential tasks and 3 servers (the exact settings can be found in table 2 for the tasks and table 1 for the servers).

Figure 2 shows the best possible allocation if tasks have fixed resource requirements. The resource speeds were chosen such to the minimum total resource usage that the task would require from the deadline. Here, 9 of the tasks are run, resulting in a total social welfare of 980 due to the limitation of the server's computation and the task requirement not being balanced.

In contrast to this, Figure 3 depicts the optimal allocation if elastic resources are considered. Here, it is evident that all of the resources are used by the servers whereas the fixed (in figure 2) cant do this. In total, the elastic approach manages to schedule all 12 tasks within the resource constraints, achieving a total social welfare of 1200 (an 19% improvement over the fixed approach).

The figures represent resource usage of the servers by the three bars relating to each of this resources (storage, CPU and bandwidth). For each task that is allocated to the server, the percentage of the resource's used is bar size. Then, for the tasks that are assigned to corresponding servers, the percentage of used resources are also depicted.

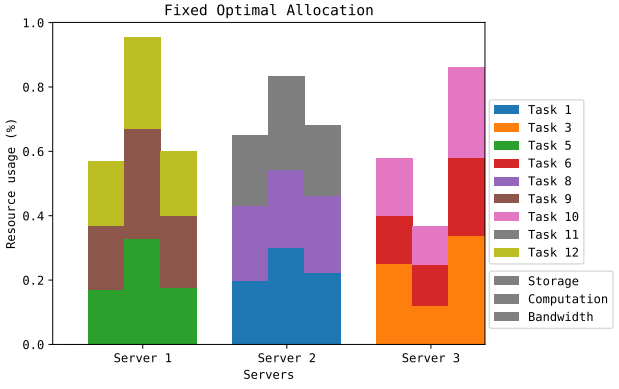


Figure 2: Optimal solution with fixed resources. Due to not being able to balance out the resources, bottlenecks on the server 1 and 2's computation have occurred

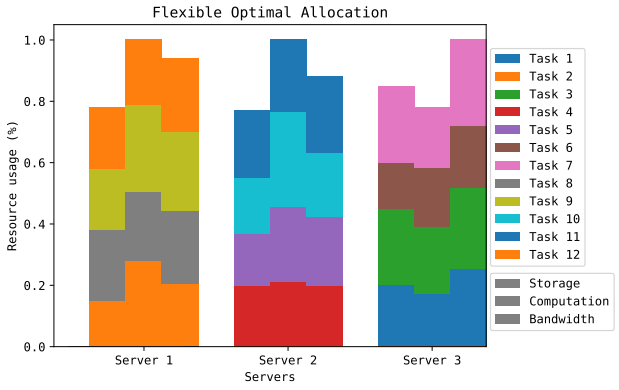


Figure 3: Optimal solution with elastic resources. Compared to the fixed allocation, the elastic allocation is able to fully use all of its resources

Name	S_i	W_i	R_i
Server 1	400	100	220
Server 2	450	100	210
Server 3	375	90	250

Table 1: Servers - Table of server attributes

Name	v_j	s_j	w_j	r_j	d_j	$s_j^{'}$	$w_j^{'}$	$r_j^{'}$
Task 1	100	100	100	50	10	30	27	17
Task 2	90	75	125	40	10	22	32	15
Task 3	110	125	110	45	10	34	30	17
Task 4	75	100	75	35	10	27	21	13
Task 5	125	85	90	55	10	24	28	17
Task 6	100	75	120	40	10	20	32	16
Task 7	80	125	100	50	10	31	30	19
Task 8	110	115	75	55	10	30	22	20
Task 9	120	100	110	60	10	27	29	24
Task 10	90	90	120	40	10	25	30	17
Task 11	100	110	90	45	10	30	26	16
Task 12	100	100	80	55	10	24	24	22

Table 2: Tasks - Table of task attributes, the columns for resource speeds ($s_j^{'}, w_j^{'}, r_j^{'}$) is for fixed speeds which the flexible allocation does not take into account. The fixed speeds is the minimum required resources to complete the task within the deadline constraint.

4 FLEXIBLE RESOURCE ALLOCATION MECHANISMS

In this section, we propose several mechanisms for solving the resource allocation problem with elastic resources. First, we discuss a centralized greedy algorithm (detailed in Section 4.1) with a $\frac{1}{|J|}$ performance guarantee and polynomial run-time. Then, we consider settings where task users are self-interested and may either report their task values and requirements strategically or may wish to limit the information they reveal to the mechanism. To deal with such cases, we propose two auction-based mechanisms, one of which can be executed in a decentralized manner (in Sections 4.2 and 4.3).

4.1 Greedy Mechanism

As solving the allocation problem with elastic resources is NP-hard, we here propose a greedy algorithm (Algorithm 1) that considers tasks individually, based on an appropriate prioritisation function.

More specifically, the greedy algorithm does this in two stages; the first sorts the tasks and the second allocates them to servers. A value density function is applied to each of the task based on its attributes: value, required resources and deadlines. Stage one uses this function to sort the list of tasks. The second stage then iterates through the tasks in the given order, applying two heuristics to each task: one to select the server and another to allocate resources. The first of these heuristics, called the server selection heuristic, works by checking if a server could run the task if all of its resources were to be used for meeting the deadline constraint (eq 5) then calculating how good it would be for the job to be allocated to the server. The second heuristic, called the resource allocation heuristic, finds the best permutations of resources to minimise a formula, i.e., the total percentage of server resources used by the task.

In this paper we prove that the lower bound of the algorithm is $\frac{1}{|J|}$ (where $|J|$ is the number of jobs) using the value of a task as the value density function and using any feasible server selection and resource allocation heuristic. However we found that the task value heuristic is not the best heuristic as it does not consider the effect of the deadline or resources used for a job. In practice, the following heuristic often works better: $\frac{v_j \cdot (s_j + w_j + r_j)}{d_j}$. For the server selection heuristic we use $argmin_{\forall i \in I} S_i^{'} + W_i^{'} + R_i^{'}$, where $S_i^{'}$, $W_i^{'}$, $R_i^{'}$ are the server's available storage, computation and bandwidth resources respectively. While for the resource allocation heuristic we use $min \frac{W_i^{'}}{w_j^{'}} + \frac{R_i^{'}}{s_j^{'} + r_j^{'}}$.

Theorem 4.1. *The lower bound of the greedy mechanism is $\frac{1}{n}$ of the optimal social welfare*

Proof. Taking the value of a task as the value density function, the first task allocated will have a value of at least $\frac{1}{n}$ total values of all jobs. As the allocation of resources for a task is not optimal, allocation of subsequent tasks is not guaranteed. Therefore, as the optimal social welfare must be the total values of all jobs or lower then the lower bound of the mechanism must be $\frac{1}{n}$ of the optimal social welfare. □

In figure 4, an example allocation using the algorithm is shown using the model from tables 1 and 2. The algorithm uses the recommend heuristic proposed above and allows for all tasks to be allocated achieving 100% of the flexible optimal in figure 3.

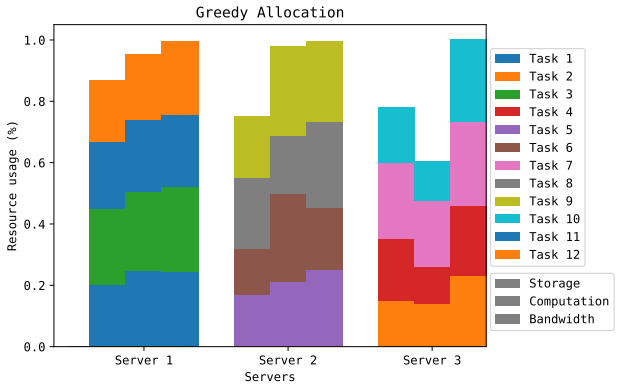


Figure 4: Example Greedy allocation using model from table 2 and 1

Algorithm 1 Greedy Mechanism

Require: J is the set of tasks and I is the set of servers
Require: $S_i^{'}$, $W_i^{'}$ and $R_i^{'}$ is the available resources (storage, computation and bandwidth respectively) for server i.
Require: $\alpha(j)$ is the value density function of a task
Require: $\beta(j, I)$ is the server selection function of a task and set of servers returning the best server, or $\emptyset$ if the task is not able to be run on any server
Require: $\gamma(j, i)$ is the resource allocation function of a task and server returning the loading, compute and sending speeds
Require: $sort(X, f)$ is a function that returns a sorted list of elements in descending order, based on a set of elements and a function for comparing elements

```
J' ← sort(J, α)
for all j ∈ J' do
    i ← β(j, I)
    if i ≠ ∅ then
        s'_j, w'_j, r'_j ← γ(j, i)
        x_{i,j} ← 1
    end if
end for
```

Theorem 4.2. *The time complexity of the greedy algorithm is $O(|J|\,|I|)$, where $|J|$ is the number of tasks and $|I|$ is the number of servers. Assuming that the value density and resource allocation heuristics have constant time complexity and the server selection function is $O(|I|)$.*

Proof. The time complexity of the stage 1 of the mechanism is $O(|J|\log(|J|))$ due to sorting the tasks and stage 2 has complexity $O(|J|\,|I|)$ due to looping over all of the tasks and applying the server selection and resource allocation heuristics. Therefore the overall time complexity is $O(|J|\,|I| + |J|\log(|J|) = O(|J|\,|I|)$. □

4.2 Critical Value Auction

Due to the problem case being non-cooperative, if the greedy mechanism was used to allocate resources such that the value is the price paid. This is open to manipulation and misreporting of task attributes like the value, deadline or resource requirements. Therefore in this section we propose an auction that is weakly-dominant for tasks to truthfully report it attributes.

Single-Parameter domain auctions are extensively studied in mechanism design [16] and are used where an agent's valuation function can be represented as single value. The task price is calculated by finding the task's value such that if the value were any smaller, the task could not be allocated. This value is called the critical value. This has been shown to be a strategyproof [17] (weakly-dominant incentive compatible) auction so it is a weakly-dominant strategy for a task to honestly reveal its value.

The auction is implemented using the greedy mechanism from section 4.1 to find an allocation of tasks using the reported value. Then for each task allocated, the last position in the ordered the task list such that the task would still allocated is found. The critical value of the task is then equal to the inverse of the value density function where the density is the density of the next task in the list after that position.

In order that the auction is strategyproof, the value density function is required to be monotonic so that misreporting of any task attributes will result in the value density decreasing. Therefore a value density function of the form $\frac{v_j d_j}{\alpha(s_j, w_j, r_j)}$ must be used so that the auction is strategyproof.

Theorem 4.3. *The value density function $\frac{v_j d_j}{\alpha(s_j, w_j, r_j)}$ is monotonic for task j assuming the function $\alpha(s_j, w_j, r_j)$ is monotonic decreasing.*

Proof. In order to misreport the task private value and deadline must be less than the true value. The opposite is true for the required resources (storage, compute and result data) with the misreported value being greater than the true value. Therefore the α function will increase as the resource requirements increase as well, meaning that density will decrease. □

4.3 Decentralised Iterative Auction

VCG (Vickrey-Clark-Grove) auction [21] [5] [8] is proven to be economically efficient, budget balanced and incentive compatible. A task's price is found by the difference of the social welfare for when the task exists compared to the social welfare when the task doesn't exist. Our auction uses the same principle for pricing by finding the difference between the current server revenue and the revenue when the task is allocated (at £0).

The auction iteratively lets a task advertise its requirements to all of the servers who respond with their price for the task. This price is equal to the server's current revenue minus the solution to the the problem in section 4.3.1 plus a small value called the price change variable. Being the reverse of the VCG mechanism, such that the price is found for when the task exists rather than when it doesn't exist. The price change variable allows for the increase in the revenue of the server and is can be chosen by the server. Once all of the server have responded, the task can compare the minimum server price to its private value. If the price is less then the task will accept the servers with the minimum price offer, otherwise the task will stop looking as the price for the task to run on any server is greater than its reserve price.

To find the optimal revenue for a server m given a new task p and set of currently allocated tasks N has a similar formulation to section 3.2. With an additional variable is considered, a task's price being p_n for task n.

4.3.1 Server problem case.

$$\max \sum_{\forall n \in N} p_n x_n \tag{11}$$

$$\text{s.t.} \tag{12}$$

$$\sum_{\forall n \in N} s_n x_n + s_p \leq S_m, \tag{13}$$

$$\sum_{\forall n \in N} w_n^{'} x_n + w_p \leq W_m, \tag{14}$$

$$\sum_{\forall n \in N} (r_n^{'} + s_n^{'}) \cdot x_n + (r_p^{'} + s_p^{'}) \leq R_m, \tag{15}$$

$$\frac{s_n}{s_n^{'}} + \frac{w_n}{w_n^{'}} + \frac{r_n}{r_n^{'}} \leq d_n, \quad \forall n \in N \cup \{p\}, \tag{16}$$

$$0 \leq s_n^{'} \leq \infty, \quad \forall n \in N \cup \{p\} \tag{17}$$

$$0 \leq w_n^{'} \leq \infty, \quad \forall n \in N \cup \{p\} \tag{18}$$

$$0 \leq r_n^{'} \leq \infty, \quad \forall n \in N \cup \{p\} \tag{19}$$

$$x_n \in \{0, 1\}, \quad \forall n \in N \tag{20}$$

The objective (Eq.(11)) is to maximize the price of all tasks (not including the new task as the price is zero). The server resource capacity constraints are similar to the constraints in the standard model set out in section 3.2 however with the assumption that the task k is running so there is no need to consider if the task is running or not. The deadline and non-negative resource speeds constraints (5, 6, 7 and 8) are all the same equation with the new task included with all of the other tasks. The equation to check that a task is only allocated to a single server is not included as only server i considers the task k's price.

In auction theory, four properties are considered: Incentive compatible, budget balanced, economically efficient and individual rationality.

- Budget balanced - Since the auction is run without an auctioneer, this allows for the auction to be run in a decentralised way resulting in no "middlemen" taking some money so all revenue goes straight to the servers from the tasks
- Individually Rational - As the server need to confirm with the task if it is willing to pay an amount to be allocated, the task can check this against its secret reserved price preventing the task from ever paying more than it is willing
- Incentive Compatible - Misreporting can give a task as if the task can predict the allocation of resources from server to tasks then tasks can misreport so to be allocate to a certain server that otherwise would result in the task being unallocated.
- Economic efficiency - At the begin then task are almost randomly assigned in till server become full and require kicking tasks off, this means that allocation can fall into a local price maxima meaning that the server will sometime not be 100% economically efficient.

Algorithm 2 Decentralised Iterative Auction

Require: I is the set of servers
Require: J is the set of unallocated tasks, which initial is the set of all tasks to be allocated
Require: $P(i,k)$ is solution to the problem in section 4.3.1 using the server i and new task k. The server's current tasks is known to itself and its current revenue from tasks so not passed as arguments.
Require: $R(i,k)$ is a function returning the list of tasks not able to run if task k is allocated to server i
Require: $\leftarrow_R$ will randomly select an element from a set
  while $|J| > 0$ **do**
    $j \leftarrow_R J$
    $p, i \leftarrow argmin_{i \in I} P(i,j)$
    if $p \leq v_j$ **then**
      $p_j \leftarrow p$
      $x_{i,j} \leftarrow 1$
      for all $j^{'} \in R(i,j)$ **do**
        $x_{i,j^{'}} \leftarrow 0$
        $p_j^{'} \leftarrow 0$
        $J \leftarrow J \cup j^{'}$
      end for
    end if
    $J \leftarrow J \setminus \{j\}$
  end while

The algorithm 2 is a centralised version of the decentralised iterative auction. It works through iteratively checking a currently unallocated job to find the price if the job was currently allocated on a server. This is done through first solving the program in section 4.3.1 which calculates the new revenue if the task was forced to be allocated with a price of zero. The task price is equal to the current server revenue − new revenue with the task allocated + a price change variable to increase the revenue of the server. The minimum price returned by $P(i,k)$ is then compared to the job's maximum reserve price (that would be private in the equivalent decentralised algorithm) to confirm if the job is willing to pay at that price. If the job is willing then the job is allocated to the minimum price server and the job price set to the agreed price. However in the process of allocating a job then the currently allocated jobs on the server could be unallocated so these jobs allocation's and price's are reset then appended to the set of unallocated jobs.

4.4 Attributes of proposed algorithms

In table 3, the important attributes for the proposed algorithm

Attribute	GM	CVA	DIA
Truthfulness		Yes	No
Optimality	No	No	No
Scalability	Yes	Yes	No
Information requirements from users	All	All	Not the reserve value
Communication over heads	Low	Low	High
Decentralisation	No	No	Yes

Table 3: Attributes of the proposed algorithms: Greedy mechanism (GM), Critical Value auction(CVA) and Decentralised Iterative auction (DIA)

5 EMPIRICAL EVALUATION

To test the algorithms presented in section 4, synthetic models have been used to generate a list of tasks and servers.

The synthetic models have been handcrafted with each attribute being generated from a gaussian distribution with a mean and standard deviation.

To compare the greedy algorithm to the optimal elastic allocation, a branch and bound was implemented to solve the problem in section 3.2. In order to compare to fixed speed equivalent models, the minimum total resource required to run the job is found and set as the resource speeds for all of the tasks, with the optimal solution for running the job with the fixed speeds is found as well. To implement the greedy mechanism, the value density function was $\frac{v_j}{s_j+w_j+r_j}$, server selection was $argmin_{\forall i \in I} S_i^{'} + W_i^{'} + R_i^{'}$ and the resource allocation was $mins_j^{'} + w_j^{'} + r_j^{'}$ for job j and servers I.

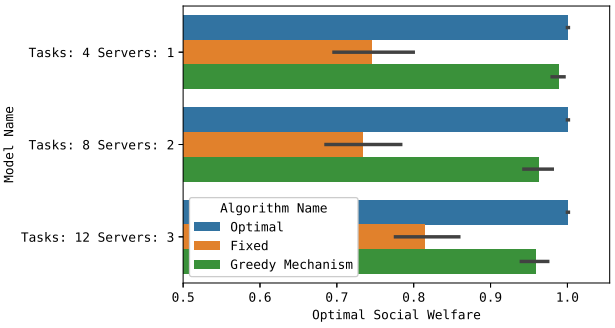


Figure 5: Comparison of the social welfare for the greedy mechanism, optimal, relaxed problem, time limited branch and bound

As figure 5 shows, the greedy mechanism achieves 98% of the optimal solution for the small models, the mechanism achieves within 95% for larger models. In comparison, the fixed allocation achieves 80% of the optimal solution and always does worse than the social welfare of the greedy mechanism.

Figure 6 compares the social welfare of the auction mechanisms: vcg, fixed resource speed vcg, critical value auction and the decentralised iterative auction with different price change variables.

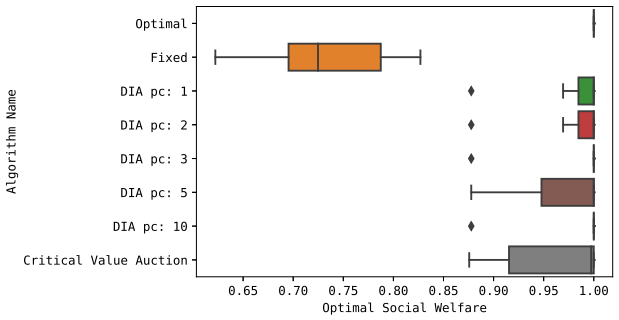


Figure 6: Comparison of the social welfare for the auction mechanisms

VCG is an economically efficient auction that requires the optimal solution to the problem in section 3.2.

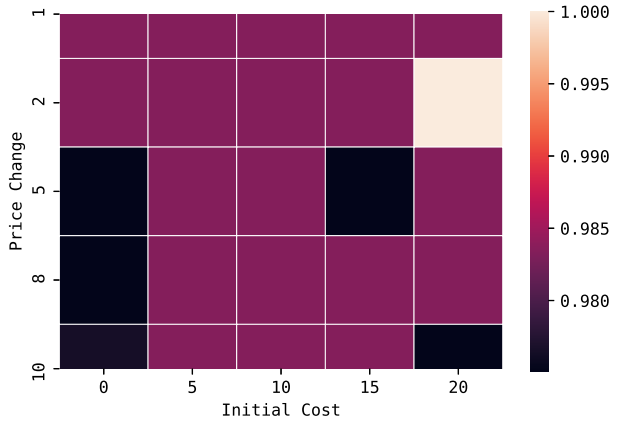


Figure 7: Average number of rounds with a price change variables and task initial cost

Within the context of edge cloud computing, the number of rounds for the decentralised iterative auction is important to making it a feasible auction as it is proportional to the time required to run. We investigated the effect of two heuristic on the number of rounds and social welfare of the auction; the price change variable and initial cost heuristic. With an auction using as minimum heuristic values for the price change and initial cost, figure 7, on average 400 rounds were required for the price to converge while an auction using a price change of 10 and initial cost of 20 means that only on average 80 rounds are required, 5x less. But by using high initial cost and price change heuristics, this can prevent tasks from being allocated, figure 8, shows that the difference in social welfare is only 2% from minimum to maximum heuristics.

6 CONCLUSIONS

In this paper, we studied a resource allocation problem in edge clouds, where resources are elastic and can be allocated to tasks at varying speeds to satisfy heterogeneous requirements and deadlines.

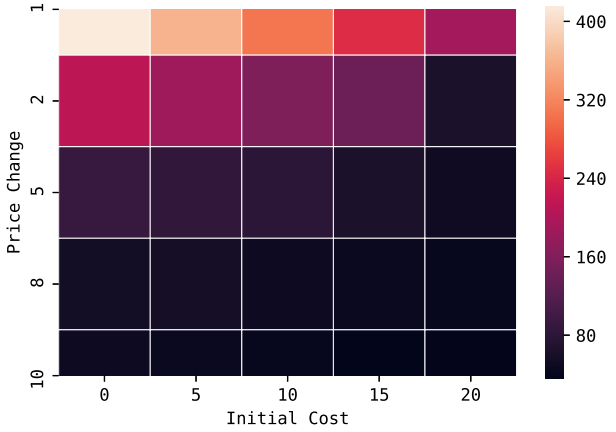


Figure 8: Average social welfare with a price change variables and task initial cost

To solve the problem, we proposed a centralized greedy mechanism with a guaranteed performance bound, and a number of auction-based mechanisms that also consider the elasticity of resources and limit the potential for strategic manipulation. We show that explicitly taking advantage of resource elasticity leads to significantly better performance than current approaches that assume fixed resources.

In future work, we plan to consider the dynamic scenario where tasks arrive and depart from the system over time, and to also consider the case where task preemption is allowed.

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