Heuristic-Driven Resource Allocation in Vehicular Fog Computing via Reinforcement Learning and Gradient Optimization

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***Abstract*—Vehicular Fog Computing(VFC) which utilizes the potential resources between the cloud and the edge of Vehicular Networks to improve the ability to compute for the edge in fog is a significant development of intelligent transportation. VFC has characteristics: low latency, high dynamic, a large number of nodes, heterogeneity, and so on. Due to decentralization and high mobility, the resource is hard to manage. High mobility is a big challenge for resource allocation. Some requests require resource vehicles to stay in the fog during process time. Vehicles in processing leave fog will cause request failure. Therefore, in this article, the problem of reducing the probability of losing resource vehicles in resource allocation is formulated. Then a heuristic algorithm that considers the resource amount, position, and mobility is proposed to sort the resource vehicle in the pool, and reinforcement learning with the gradient method is used to optimize the heuristic algorithm. The simulated result shows that the algorithm can reduce the probability of losing resource vehicles while the request is being processed.**

I. Introduction

Over the last two decades, mobile communication changed our lifestyle, which transmits more information quickly between more things. Meanwhile, the automotive industry is also developed by technological innovations [4]. Vehicles have more sensors and stronger computing ability. Vehicular Cloud Computing which is controlled by the cloud uses vehicles as servers to provide computation resources and data. Vehicular networks are recognized as a significant component of intelligent transportation systems [8] and they support various mobile services. With the development of more advanced technologies and equipment, more applications and services come out(such as self-driving) that increase the demand for more computing and data with low latency.

Fog is a new layer between the cloud and the edge of the network. Vehicular Fog Computing (VFC) extends the Vehicular Cloud Computing (VCC) paradigm to the edge of the vehicular network. VFC using vehicles as nodes has closer computing resources which do not need to communicate with the cloud bringing out low latency. Due to the dispersed of vehicles, aggregating idle computing resources of the individual vehicles and the computing resources of Road Sides Units(RSU) can enhance the Quality Of Services(Qos) greatly [1].

Although VFC has a huge opportunity for computing resources, its heterogeneity and mobility of vehicular nodes are challenges. The challenges stem from the heterogeneity of VFC and the high mobility of vehicular nodes. As vehicles move at high speeds and frequently change location, ensuring continuity and quality of service becomes a significant challenge. Furthermore, the diversity in computation and storage resources among vehicles raises the question of how to efficiently manage and schedule these resources to meet the needs of different applications.

Some requests require not losing a single resource vehicle during processing time. If a resource vehicle leaves, it will cause the request to fail and need to send the request again. Due to the high mobility of VFC, the situation become more often than traditional resource allocation. To reduce the probability, in this article, a heuristic-driven reinforcement learning and gradient optimization (HRG)algorithm is proposed. The heuristic algorithm considers the matching of resource and request, the distance between controller(RSU) and resource vehicles, and the predicted stay time which is calculated by the position changing. The controller will sort the resource vehicles when receiving requests by the heuristic algorithm, and service the request with resource vehicles in sorted order. According to the result of request processing, the heuristic algorithm will be optimized. simulations are used to evaluate the effect of the proposed algorithm. To get the most generalized results possible, simulations use an actual map, different densities of vehicles, and different random vehicle trips.

II. Background

A. Vehicular Network

The vehicular network is an emerging network. In vehicular networks, the nodes are usually vehicles and equipment on roads, which have high mobility. VANETs also called Vehicular Ad Hoc Networks are a subclass of the MANETs also called Mobile Ad Hoc Networks. VANETs provide wireless connection in vehicles to vehicles (V2V); vehicles to infrastructure (V2I); mix V2I and V2V. In VANETs, they communicate by a variety of wireless communication technologies, such as short-range radio, cellular, and WiMax.

B. Vehicular Cloud Computing

Vehicular cloud computing (VCC) is a distributed computing paradigm which has the advantage of cloud computing and vehicular networks. In VCC, vehicles are mobile nodes which can provide computation resources and process data to the other vehicles, as well as centralized to the cloud.

C. Vehicular Edge Computing

Vehicular edge computing (VEC) uses edge devices, such as on-board units (OBU) in vehicles, or RSU, and other forms of edge infrastructure to process and store data, rather than relying on centralized remote cloud infrastructure. VEC extends cloud capabilities and services to the edge of the network for a wide range of applications.

D. Vehicular Fog Computing

Fog computing architecture (the fog) distributes the tasks from the distant central management system in the cloud to the intermediate nodes which contain computational resources, to reduce the latency caused by transmitting messages between the front-end IoT devices and the back-end cloud [13].

VFC emerged as a way to combine the benefits of fog computing and vehicular networks to provide services and applications. Vehicles covered the vehicular network as fog nodes while providing decentralized local resources. The main characteristics of the Fog are Low latency, Wide-spread geographical distribution, a large number of nodes and heterogeneity [9]. Compared with VCC, the computation resource is typically at the edge of the network such as OBU or RSU rather than the remote cloud, so VFC has shorter transport distances, which come with less latency. Besides, fog computing has lower costs on deployment compared with cloud computing [10].

III. Related Works

Similar to the collaboration of the fog nodes concept, there are some offloading techniques [11] [12]. They introduce models that partition the fog landscape into distinct fog clusters, each one encompassing a centralized fog control node along with other distributed fog units. Furthermore, every individual fog unit embodies a visualized fog node that's equipped with computational, networking, and storage capabilities which are essential for coordinating an assortment of terminal IoT devices. [11]Using Maximal Resource Utilization-Based Allocation and Task Priority-Based Resource Allocation based on the task process time, but did not consider the mobility of the fog node.

In [1], they consider vehicles as infrastructures for communication and computation and propose a novel system of VFC. Four scenarios about utilizing moving and parked vehicles were provided. Two of them is using moving vehicles as infrastructures and the others are using parking vehicles. Each type of vehicle can be used to communicate and compute.

Moving vehicles transmit information by moving and communicating with different vehicles by using VANETs. Slow-moving vehicles work with RSU as local cloudlets and RSU connect to remote clouds. This hybrid cloud can provide computation capability to vehicles.

Parked vehicles can serve as static backbones and service infrastructures to improve connectivity. Besides, parked vehicles are able to service large computation demands.

Chaogang Tang, Shixiong Xia, Qing Li, Wei Chen, and Weidong Fang [2] propose pooling the vehicles together to share their computing resources in a community. Meanwhile, with the development of VFC, vehicles have more choices to join communities at the same time, they provide a genetic algorithm-based strategy to optimize that process depending on how much benefit they can earn by joining the community.

Compared to other wireless networks, vehicular networks is a highly dynamic topology, short transmission time and so on. Pereira et al. [4] propose an allocation and management resource policy for vehicular cloud(NANCY) to decide if to allocate the available resource to the request, which is based on the mathematical method Multiple Attribute Decision.

Lee and Lee [5] suggest utilizing parked vehicles to minimize service latency and present a heuristic algorithm that combines with reinforcement learning to solve the solutions the formulation set from the problem of allocating the limited fog resources.

IV. System Model

In an intelligent urban area, many vehicles are moving on the road. Each Roadside Unit(RSU) as a controller in fog maintained a resource pool and allocated resources. RSU will broadcast messages periodically to update vehicle information. When vehicles get into the RSU range and get the messages, they will send a message to tell RSU what and how many resources they can offer to the resource pool. While the vehicles are in the RSU range, they will keep updating their coordinate. If RSU does not receive the update message from the vehicle in a certain time, the vehicle will be removed from the resource pool. When vehicles have a request to the pool, they will send a message to RSU with what and how many resources they need and how long they need. When RSU revises the request, it will allocate resources from the pool to it. In my scenario, each request can be served by more than one resource vehicle, and each resource and resource vehicle can be allocated to more than one request.

In reality, some time-sensitive requests do not allow disconnect with resource vehicles while the request is in processing, otherwise, it will cause the request to fail. The proposal of the article object to reduce the probability of this kind of failure.

V. Heuristic-driven resource allocation via Reinforcement Learning and Gradient Optimization

A. Heuristic-driven resource allocation

In my scenario, RSU will calculate the failure rate(λ_{failure}) at each certain time($t_{\text{calculate}}$), and update all the vehicle information in fog at each certain time(t_{update}). There are three kinds of resources in the resource pool. The request includes what and how many resources it needs (R^1_{request},R^2_{request},R^3_{request}), and how long it need(t_{need}). When a serving vehicle leaves the resource pool while the request is still in t_{need}, the number of failures (N_{failure}) plus 1, N_{total} is total request in $t_{\text{calculate}}$. After each $t_{\text{calculate}}$, RSU have a $\lambda_{\text{failure}} = N_{\text{failure}} \div N_{\text{total}}$, and then reset N_{failure}, N_{total} to zero.

There are three parts in the heuristic algorithm: using Q,D, and T of each resource vehicle to sort the resource vehicle pool.

The first part Q is sorted by resource. The quantity of the requested resources($R^{\text{a}}_{\text{request}}$) and the quantity of each available($R^{\text{a}}_{\text{serve}}$) resource will be compared. The same one will have the lowest scores. $R^{\text{a}}_{\text{request}}$ bigger than $R^{\text{a}}_{\text{serve}}$ will have higher scores than $R^{\text{a}}_{\text{request}}$ smaller than $R^{\text{a}}_{\text{serve}}$. The smaller differences will have lower scores. The purpose of this section is This part aims to use as less as possible vehicles to serve the requests. Each resource will have a score .Q is the sum of all scores of resources in a vehicle(1).

$$Q = \sum_{1}^{\text{a}} Q_{\text{a}} \tag{1}$$

The second part D is sorted by distance. The distance between the resource vehicle and RSU can be calculated by their coordinate(2).

$$D = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2} \tag{2}$$

The third part T is sorted by the predicted stay time of the resource vehicle. Assume the vehicle moves in a straight line. It updates its coordinate twice in t_{update}. Then RSU can calculate the slope and intercept of the equation of the line given the two points $(x1, y1)$ and $(x2, y2)$. Substitute the equation of the line into the equation of the circle(RSU coordinate$(x0, y0)$, radius(r)) to obtain a quadratic equation. Solve this equation to find the intersection($(x_\alpha, y_\alpha), (x_\beta, y_\beta)$) of the line and the circle(3). Use (2) to find $dist1 : ((x_\alpha, y_\alpha), (x1, y1))$, $dist2 : ((x_\alpha, y_\alpha), (x2, y2))$, $dist3 : ((x_\beta, y_\beta), (x1, y1))$, $dist4 : ((x_\beta, y_\beta), (x2, y2))$. Using (4) (5) get T.

$$(\frac{(y2-y1)}{(x2-x1)} * x + (y1 - \frac{(y2-y1)}{(x2-x1)} * x1) - y0)^2 + (x - x0)^2 = r^2 \tag{3}$$

$$dist = \begin{cases} dist2, & \text{if } dist2 < dist1 \\ dist4, & \text{if } dist4 < dist2 \end{cases} \tag{4}$$

$$T = \frac{dist}{v} = \frac{dist}{\frac{\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}}{t_{\text{update}}}} \tag{5}$$

The RSU will sort each part to get three sorted lists and the smallest score on the top. Q_0 , D_0, T_0 are the serial numbers of each sorted list. Now each resource vehicle has (Q_0 , D_0, T_0 $\in$amount of all resource vehicles) . RSU will use (6) get S. k1,k2,k3 is default 10. Finally, RSU will use S from each resource vehicle to sort the resource pool for the request and allocate from the smallest S resource vehicle. **Algorithm 1** shows the procedure of heuristic-driven resource allocation.

$$S = k1 * Q_0 + k2 * D_0 + k3 * T_0 \tag{6}$$

Algorithm 1 Heuristic Resource Allocation

1: $k_1, k_2, k_3 \leftarrow 10, 10, 10$
2: **procedure** HEURISTICMETHOD(RSU_data, $vehicles$)
3: **for all** $vehicle \in vehicles$ **do**
4: $Q \leftarrow$ CALCULATEQ()
5: $D \leftarrow$ CALCULATEDISTANCE()
6: $T \leftarrow$ CALCULATETIME()
7: $vehicle.score \leftarrow k_1 \cdot Q + k_2 \cdot D + k_3 \cdot T$
8: **end for**
9: SORTVEHICLESBYSCORE(vehicles)
10: $allocations \leftarrow$ ALLOCATERESOURCES($vehicles$)
11: **return** $allocations$
12: **end procedure**

B. Reinforcement Learning and Gradient Optimization

Using Reinforcement Learning and Gradient Optimization to optimize the sorting function(6), where $k1$, $k2$, and $k3$ are weight parameters generated from a normal distribution. The goal is to minimize the failure rate λ_{failure}, reflecting the efficacy of resource allocation.

The weight parameters $k1$, $k2$, and $k3$ are generated based on three normal distributions, each normal distribution has two parameters: (μ mean, σ standard deviations). They are defult$(10, 1)$ at the beginning. The algorithm operates iteratively, adjusting the parameters of normal distributions based on the observed λ_{failure}. In each iteration, the weight parameters are generated from the updated normal distributions. The algorithm then executes for a certain period $t_{\text{calculate}}$. After that the λ_{failure} is observed. Depending on the change in λ_{failure} between iterations, the means and standard deviations of the parameters are updated. If λ_{failure} decreases (indicating performance improvement), the mean and standard deviation of each weight parameter change like (7). If λ_{failure} increases (indicating performance decline), the mean and standard deviation of each weight parameter change like (8). $\mu_{\text{tcalculate}}$ and $\sigma_{\text{tcalculate}}$ are the mean and standard deviation of correspond k in precious $t_{\text{calculate}}$. ω is the update rate. **Algorithm 2** shows the procedure of Reinforcement Learning and Gradient Optimization for resource allocation. tion for Resource Allocation

$$\begin{cases} \mu_{\text{new}} = \mu_{\text{current}} + \omega * (\lambda^{\text{old}}_{\text{failure}} - \lambda^{\text{new}}_{\text{failure}}) * (\mu_{\text{tcalculate}} - \mu_{\text{current}}) \\ \sigma_{\text{new}} = \sigma_{\text{current}} + \omega * (\lambda^{\text{old}}_{\text{failure}} - \lambda^{\text{new}}_{\text{failure}}) * (\sigma_{\text{tcalculate}} - \sigma_{\text{current}}) \end{cases} \tag{7}$$

$$\begin{cases} \mu_{\text{new}} = \mu_{\text{current}} - \omega * (\lambda^{\text{new}}_{\text{failure}} - \lambda^{\text{old}}_{\text{failure}}) * (\mu_{\text{tcalculate}} - \mu_{\text{current}}) \\ \sigma_{\text{new}} = \sigma_{\text{current}} - \omega * (\lambda^{\text{new}}_{\text{failure}} - \lambda^{\text{old}}_{\text{failure}}) * (\sigma_{\text{tcalculate}} - \sigma_{\text{current}}) \end{cases} \tag{8}$$

VI. PERFORMANCE EVALUATION

The approach: Heuristic-Driven Resource Allocation via Reinforcement Learning and Gradient Optimization was evaluated by simulation. For the simulator tool, we used VEINS (5.0) [14], SUMO (1.2.0) [15], and OMNeT++ (5.5.1) [16].

Algorithm 2 Reinforcement Learning and Gradient Optimization for Resource Allocation

Initialize k_1, k_2, k_3 with default normal distributions $N(10, 1)$
$\lambda_{\text{old\_failure}} \leftarrow$ initial failure rate
$\omega \leftarrow$ update rate
repeat
  Generate k_1, k_2, k_3 from their respect tributions
  Execute resource allocation for time t
  Observe new failure rate $\lambda_{\text{new\_failure}}$
  if $\lambda_{\text{new\_failure}} < \lambda_{\text{old\_failure}}$ **then**
    Eq(7)
  else
    Eq(8)
  end if
  Update normal distributions for k_1, k_2 and σ
  $\lambda_{\text{old\_failure}} \leftarrow \lambda_{\text{new\_failure}}$
until termination condition is met

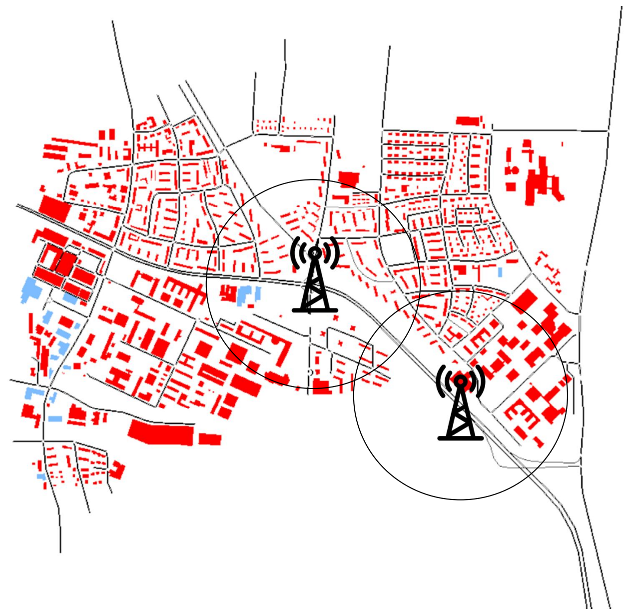

Fig. 1.

The map is an urban area map from Erlangen, Germany. The map area size is 3500*3500 m^2. Fig. 1 shows the map and the position of RSU in the simulation. The circle is the RSU communication range. The vehicle's movement was produced by pseudo-random parameters, which have random trips on the map. TABLE 1 shows the parameters setting in the simulation and evaluation.

TABLE I
SIMULATION PARAMETERS

Parameter	value
RSU Density	2
RSU Coordinate	RSU2(1250,1350,3)RSU1(1900,1900,3)
Vehicle Communication Range	500 m
RSU Communication Range	500 m
Vehicle Speed	0-120 km/h
Traffic Volume(period)	4,4.5,5 s/car arrival
Max hop count	2
RSU PHY model	IEEE 802.11p
Communication Method	V2V and V2I
Simulation time	30000 s
Request Resource	random(0,100)
Available Resource	random(0,100)
Resource Request time	random(0,60)s
signal passes obstacle	-9 dB
signal per meter	-0.4 dB
Transmission Power	20 mW
$t_{\text{calculate}}$	2000 s
t_{update}	1 s
ω Update Rate	100

A. Simulation Scenario and Methodology

RSU will send a message to all vehicles in fog in each 1s (t_{update}). When the vehicles receive the message, they will send back a message to RSU. This message has coordinates, available resources, and requested resources with request time. When the requested resources are not zero, the available resources are zero. It is 50% the request resources is not zero. When RSU receives this message, it will keep the vehicle in the resource pool, and add available resources to the pool or process the request. If RSU does not receive the message from the vehicle in 3 s, the vehicle will be deleted from the resource pool. When vehicles send a message to RSU, V2V, and V2I can be used to reach the nearest roadside unit. When RSU processes the request, if it uses a heuristic method via Reinforcement learning and gradient optimization(HRG), it will sort the resource pool and then allocate resources to the request. If RSU does not use the HRG algorithm, it will allocate the available resources in order of last come first served(STACK). RSU will calculate the λ_{failure} in each 2000s.

For simulation, the vehicle movement is generated by the tool of SUMO: randomTrips.py. Three traffic Volume situations are used in our scenario. Traffic Volume is defined by the period parameter. In our scenario, It means vehicles are generated every 4, 4.5, and 5 seconds. All the simulation times are 30000s. For the experiment, I applied STACK, HRG without reinforcement learning and gradient optimization(H), and HRG in those three traffic volumes and got their λ_{failure}. For observation the effection of the algorithm 2. I chose traffic volumes of 5 to run three times by HRG, got all the normal distribution parameters at the end of each simulation in RSU1, and set it default for the next simulation. In the meantime record all the new parameters set by each update.

B. Performance Metrics

A few performance indicators were chosen to assess the proposal. The proposal aims to reduce the probability of losing resource vehicles while the request is being processed, so λ_{failure} is used to evaluate.

For a better assessment of the efficiency of **Algorithm 2**, record the new normal distribution parameters of weight parameter(k) in each iteration. Observe ΔP over time (9),ΔP is the different new parameter and old parameter. If it becomes stable in a short time, It means that algorithm 2 is efficient.

$$\Delta P = P_{\text{new}} - P_{\text{old}} \tag{9}$$

the following metrics:

C. Computational Complexity

For **Algorithm 1**: Heuristic algorithm, the main part is to rank vehicles by calculating different scores. The time complexity of the sorting operation itself is $O(nlogn)$, which is also the complexity of Algorithm 1.

For **Algorithm 2**: Reinforcement Learning and Gradient Optimization, the main part is to calculate the mean and standard deviation. It depends on how many k values in t_{caculate}. Therefore, it is $O(n)$.

D. Results

In my simulation, there are two RSU on the map RSU2(1250,1350,3), and RSU1(1900,1900,3) which is the lower one. Fig.2 to Fig.7 are the simulation results of three traffic volumes: 4, 4.5, and 5. Their simulation time is all $30000s$. Y-axis is λ_{failure}, and X-axis show which interval of λ_{failure} in order of time. Each interval is t_{update} long. Each graph has three lines, they are λ_{failure} changing of STACK, H, and HRG in simulation time. STACK allocates available resources in order of last come first served without Algorithm 1 and Algorithm 2. H is only Algorithm 1. HRG are both Algorithm 1 and Algorithm 2.Fig.2 and Fig.5 are traffic volumes of 4, Fig.3 and Fig.6 are traffic volumes of 4.5, and Fig.4 and Fig.7 are traffic volumes of 5. Fig.2 to Fig.4 are RSU1. Fig.5 to Fig.7 are RSU2. In average λ_{failure} of RUS 1 in traffic volumes: 4, 4.5, and 5, HRG is 4.43% less than STACK. In average λ_{failure} of RUS 2 in traffic volumes: 4, 4.5, and 5, HRG is 10.40% less than STACK. HRG and H have similar λ_{failure}.

Fig.8 to Fig.13 is the RSU1 simulation result of running three times traffic volumes: 5 by HRG. The X-axis indicates which ΔP is in order of time. The Y-axis is ΔP, which means the change between the last new setting parameters and this new setting parameters. Fig.8, Fig.10, and Fig.12 are μ(mean). Fig.9, Fig.11, and Fig.13 are σ(standard deviation). There is a trend dotted line in each graph of Fig.8 to Fig.13. It shows the direction of the data. When it has a distance from the X-axis, it means the parameter is changing. If on the positive side, it means the parameter increasing, otherwise decreasing. Fig.8 and Fig.9 are the parameters of $K1$ (6). Fig.10 and Fig.11 are the parameters of $K2$. Fig.12 and Fig.13 are the parameters of $K3$.In Fig.8, Fig.9, Fig.11, and Fig.12, their trend dotted lines are going close to the X-axis. It means the parameters are going to be stable. The optimization is coming to an end. On the other side, the trend dotted lines of Fig.10 and Fig.13 are away from the X-axis, which means μ fo $K2$ and σ fo $K3$ are still being optimized.

VII. Conclusion

This article proposes a heuristic-driven resource allocation via reinforcement learning and gradient optimization (HRG) approach. It has two parts: Algorithm 1 and Algorithm 2. According to the simulation result, HRG and H can reduce the λ_{failure} from STACK. The reinforcement learning and gradient optimization part of HRG not working well so far, but the parameters are still being optimized in simulation. It is not efficient now.

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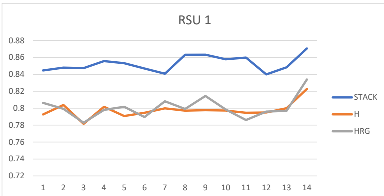
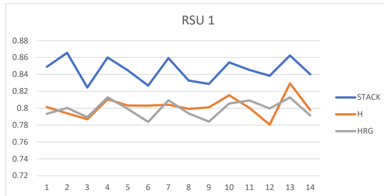


Fig. 2.



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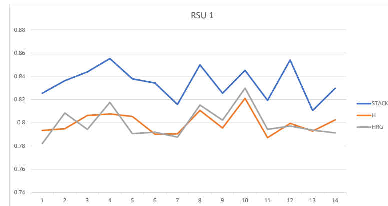

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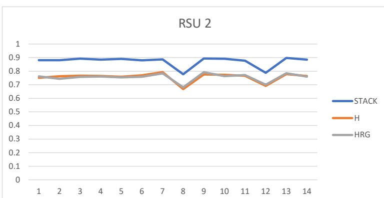

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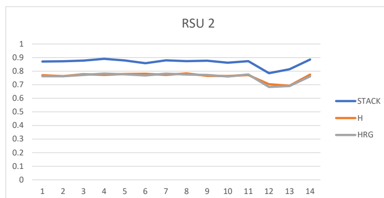

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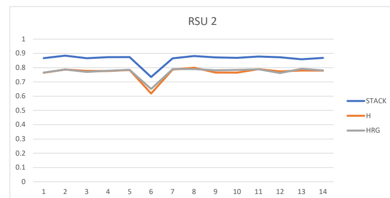

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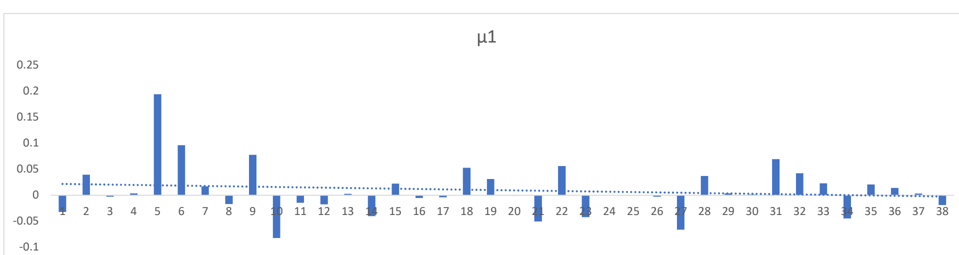

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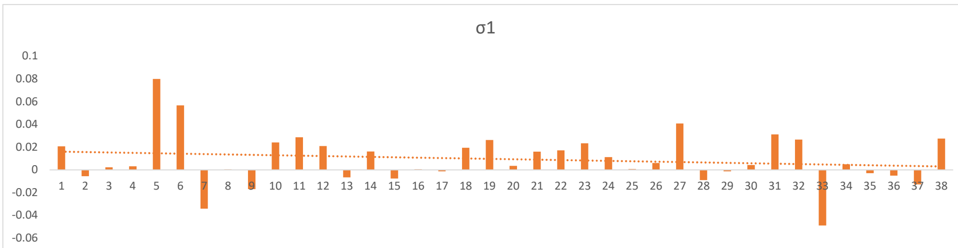
σ1
0.1
0.08
0.06
0.04
0.02
0
-0.02
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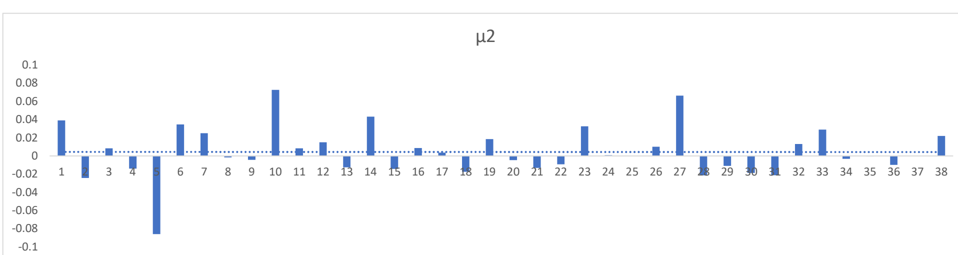
Fig. 9.


μ2
0.1
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1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38

Fig. 10.

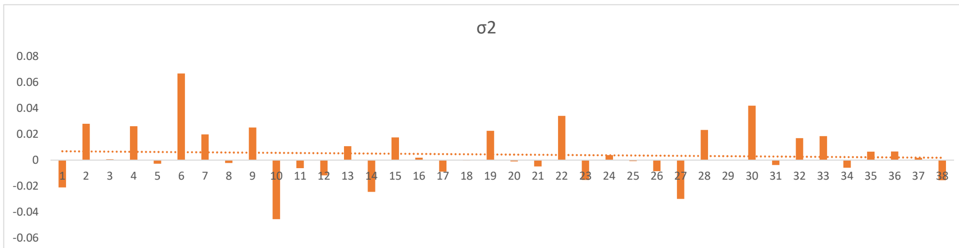
σ2
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38

Fig. 11.

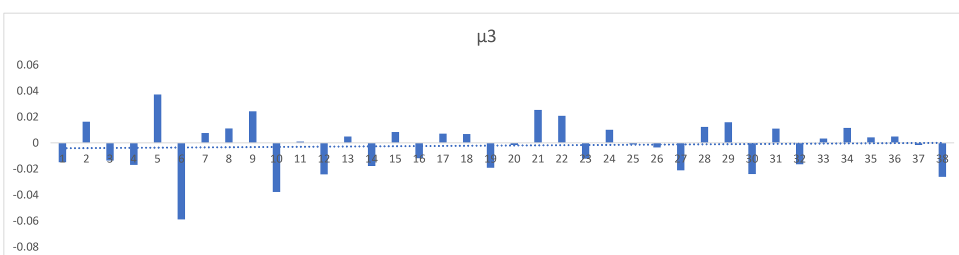
μ3
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38

Fig. 12.

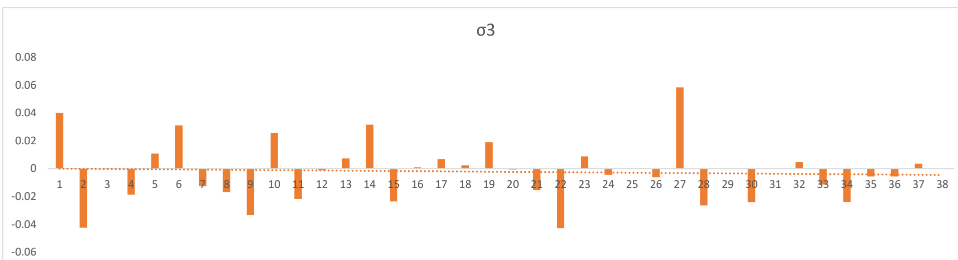
σ3
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38

Fig. 13.