# Kafka Consumer Group Autoscaler

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Abstract-Message brokers enable asynchronous communication between data producers and consumers in distributed environments by assigning messages to ordered queues. Message broker systems often provide with mechanisms to parallelize tasks between consumers to increase the rate at which data is consumed. The consumption rate must exceed the production rate or queues would grow indefinitely. Still, consumers are costly and their number should be minimized. We model the problem of determining the required number of consumers, and the partition-consumer assignments, as a variable item size bin packing variant. Data cannot be read when a queue is being migrated to another consumer. Hence, we propose the R-score metric to account for these rebalancing costs. Then, we introduce an assortment of R-score based algorithms, and compare their performance to established heuristics for the Bin Packing Problem for this application. We instantiate our method within an existing system, demonstrating its effectiveness. Our approach guarantees adequate consumption rates - something the previous system was unable to - at lower operational costs.

Index Terms—variable item size, bin packing, consumer group autoscaling, message broker

#### I. INTRODUCTION

Message Brokers are a common tool employed to fixture communication in a distributed environment [1]. This system provides with asynchronous communication between producers and consumers, and handles some of the challenges that are common within distributed and concurrent data processing.

We consider a queue or partition to be a structure within a message broker environment where messages are appended in the same order as they were produced. It is also important that this structure is capable of delivering the messages in the same order as they were produced. This consumption model is often a requirement to guarantee state consistency between two distinct distributed systems for a specific business related entity. Common applications that employ replaying a set of messages in the same order as they were produced include event-carried state transfer, and system state simulation. The former consists of having two systems reading the same set of messages in the same order to replicate an entities state within their data store [2], [3], whereas the latter is used to simulate a system's state at a given point in time by reproducing the messages up until that point [4], [5].

Two common message broker implementations, Kafka and RabbitMQ, have different ways of guaranteeing message order on consumption. Within Kafka, all the messages produced to a partition are appended and delivered in the same order as they were published. Messages can be consistently produced to the

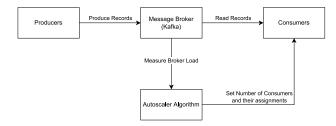


Fig. 1: On request, our algorithm determines the number of consumers and partition-consumer assignment based on the message broker's current load.

same partition if the same key is used<sup>1</sup>. As for RabbitMQ, it guarantees messages toward a queue are enqueued in the same order as they were produced. Therefore, to guarantee same order message delivery, only a single consumer can be reading messages from the queue<sup>2</sup>.

Within a distributed message broker environment, provided we are given a set of independent queues, our goal is to manage a group of consumers, so as to guarantee the rate of consumption is at least as high as the production rate.

Since message ordering is important, only one consumer can be assigned a queue, but multiple queues can be assigned the same consumer. This also implies that the maximum number of consumers is limited to the number of queues.

As each consumer represents an active computing resource, while attempting to determine the amount of parallelism required, we are also aiming to minimize the operational cost, by reducing the number of consumers.

Considering consumers as bins, and queues as items that have to be assigned a bin, this problem was modeled as a variation of the Bin Packing (BP) Problem, with the particularity that items vary in size over time. This occurs because a queue's size correlates to its current write speed, which fluctuates based on the current system's load and inevitably implies that a BP solution for a given time instant may not hold true in future instants. Figure 1 provides with a high level representation of the interacting entities.

On account of this BP variation, a new solution has to be computed at different time instants, each having different

<sup>&</sup>lt;sup>1</sup>Kafka Message Ordering: https://kafka.apache.org/documentation/#intro\_concepts and terms

<sup>&</sup>lt;sup>2</sup>RabbitMQ Message Ordering: https://www.rabbitmq.com/queues.html# message-ordering

information as to the size of each item (each queue's "current" write speed for that time instant). This might lead to a queue (item) being migrated to a different consumer (bin) when compared to the consumer group's previous configuration.

Since two consumers cannot read from the same queue concurrently, there is another cost to take into account associated to rebalancing a partition. This cost is related to the amount of data that is not being read while the queue is being rebalanced.

Provided this is the first time the variable item size bin packing variant is applied in this context, existing algorithms do not take this rebalance cost into account. Hence, in Section IV-A we propose a metric to account for a given iteration's rebalance cost (Rscore). Additionally, using the Rscore, in Section IV-B we propose four new BP heuristic algorithms that account for the rebalance costs, three of which are shown in Section VI-C to be a competitive alternative to the multi-objective optimisation problem at hand.

Furthermore, it is our belief that this model is applicable in other contexts, e.g., the Kubernetes node autoscaling problem. In Kubernetes, nodes are machines that have resources, to which pods are assigned. Each pod is independent and the node resources it consumes varies with time. Therefore, modeling nodes as bins and pods as items whose size varies over time, this problem also fits our variation of the BP problem, with the added complexity of bins being allowed to have different sizes, which is not considered in our scenario. This problem presents similar characteristics to the work elaborated in [6] and [7].

In Section II, we present applications of the Bin Packing Problem, and a comparison of existing approximation algorithms to solve the Bin Packing problem. Section III, formally defines the problem, followed by the proposed approach in Section IV. We also present in Section V an application within a message broker environment, more specifically Kafka, of autoscaling a group of consumers based on the broker's current load. We use Section VI to present and discuss the tests performed on the proposed algorithms, and the autoscaling model when applied to Kafka. Lastly, we conclude this paper through Section VII.

## II. RELATED WORK

# A. Bin Packing Applications

There are several applications where BP is used to provide with an optimal or sub-optimal solution [8]–[11]. The Virtual Machine Placement (VMP) problem, which has gained more attention due to increasing use of cloud providers to support companies' technological infrastructure. The problem can be generalized to a set of Virtual Machines (VM), each having to be assigned one of the cloud provider's Physical Machines (PM) while attempting to minimize the operational cost. A variation of BP arrises in this scenario where the items are considered ephemeral and add another temporal dimension since they have associated a start time and a duration.

Cauwer et al. [12] study BP with a temporal variant, where the tasks have an equal start time. Their aim is to minimize the unused capacity of a physical machine over time, and therefore the optimal solution for the BP problem does not necessarily provide the optimal solution in their Temporal variant of the BP problem. In addition to the time model presented by [12], Aydın et al. [13] study the case where items may have differing start times. Their objective function is more in line with the traditional BP, as it aims to minimize the number of physical machines (bins) used. Moreover, due to the increased energy costs related to machine fire-ups (switching a machine off when it is not in use and back on again when required), the authors also attempt to minimize the number of fire-ups, making their problem multi-objective.

Furini et al. in [14], study a stateful BP variant, where the time dimension is discretized into several time instants, each with tasks that have to be executing at that time, and therefore have to be assigned a PM. Their problem has an additional constraint, related to the tasks having to run uninterrupted, and therefore cannot be assigned two different bins for their execution period. Consequently, solving each discrete problem independently does not provide with an optimal arrangement, as that would require the items to be reassigned.

The variable item size variant of the bin packing problem, has also been studied by Wolke et al. [6] and Song et al. [7], due to the varying load patterns presented by VMs. Both periodically execute a reallocating controller that determines new PM assignments for each VM, while aiming to minimize the cost of having multiple PMs running, and the migration cost. The migration cost in their problem is related to a VMs memory footprint.

Xia et al. [15] considers the online bin packing problem within the context of Fog computing, to determine whether a cloudlet has the resources to offload a user's request.

Bin packing has also been applied to real-time data streaming, which is a new paradigm of data processing, where compute nodes process the data in real-time, as opposed to batch processing the data periodically. Further elaborating, when processing data in real-time, a query is executed "continuously" to provide with real-time insights as soon as a new tuple is provided. As Gulisano et al. [16] point out, a continuous query can be constructed as a direct acyclic graph, where the different operators can be distributed to different nodes, having upstream nodes communicating with their downstream conterparts to communicate the result of its operator. This also enables for a distributed execution of a query, and an elastic infrastructure capable of scaling based on the current system's load. The authors use utilization thresholds to determine how to scale its cluster of nodes.

Heinze et al. [17], use bin packing to dynamically scale in or out a set of nodes based on the current system's query load, while maintaining process latency constraints. The authors observed underutilization, due to query operators no longer occupying computing resources in host machines after task completion, and therefore, devised a re-balance policy. They acknowledge re-executing the bin packing heuristic would provide with better utilization rates, but in their scenario this was not feasible due to excessive re-balance cost, and therefore devise a re-balancing algorithm that re-places only

the operators that present minimal load in their system, until a specific condition is met. As a complement to the previous findings, [18] extends the algorithm to use reinforcement learning to improve the decision to scale out or in, based on the utilization rates and latency measurements.

## B. Approximation Algorithms

The Bin Packing (BP) problem is a well established research problem, and has been extensively reviewed in the literature. Due to the time constraints imposed by our application, this paper gives emphasis to the Approximation Algorithms that heuristically solve the problem in low-order polynomial time, as opposed to the higher time complexity Linear Programming approach.

A method is presented to classify the BP problem in [19], which will be used throughout this section. During an algorithm's execution, a bin can find itself either *open* or *closed*. In the former, the bin can still be used to add additional items, whereas in the latter, it is no longer available and has already been used.

The list of bins is indexed from left to right, and the number of bins used by an algorithm can be computed using the index of the first empty bin in the list of bins. When creating a bin, this process can be visualized as opening the lowest index of the empty bins (left-most empty bin).

Using A(L) to denote the amount of bins a certain algorithm makes use of for a configuration of items L, OPT(L) to represent the amount of bins required to achieve the optimal solution, and defining  $\Omega$  as the set of all possible lists, each with a different arrangement of their items,

$$R_A(k) = \sup_{L \in \Omega} \left\{ \frac{A(L)}{k} : k = OPT(L) \right\},\tag{1}$$

encodes a performance metric relative to the optimal number of bins used by an algorithm. The Asymptotic Performance Ratio (APR) of an algorithm  $A(R_A^\infty)$  is defined as

$$R_A^{\infty} = \limsup_{k \to \infty} R_A(k). \tag{2}$$

This is the metric that will be used throughout this section to compare the algorithms' performance.

Despite the mulititude of classes presented in [19], the only class of problems that is of interest for this paper, is the offline bin packing variant.

Offline BP algorithms are aware of the list of items that are to be assigned bins prior to its execution. As long as the set of items remains the same, items can be grouped, sorted or anything that might be convenient to the algorithm that is going to iterate over the list of items.

The Any Fit subclass of algorithms must fit the constraint: if bin j is empty, an item will not be assigned to it if the item fits into any bin to the left of j. These algorithms perform best if the list of items is sorted in a non-increasing order prior to assigning bins to the items. The offline approximation algorithms that are going to be described, follow this sorting strategy, and all but the Next Fit Decreasing (NFD) belong to this subclass of algorithms. Provided a list of sorted items, the

NFD only has a single open bin at a time, which is also the last created bin. This algorithm attempts to place the item in the right-most non-empty bin. If it does not fit, then the bin to the right is used. As shown in [20], this algorithm has as APR,

$$R_{NFD}^{\infty} \approx 1.6910. \tag{3}$$

With regards to the Worst Fit Decreasing (WFD), for each item, it attempts to assign the bin with most slack. If the size constraint is not satisfied, a new bin is assigned.

The Best Fit Decreasing (BFD) is similar to the WFD differing only on its packing strategy, wherein this algorithm attempts to place the item in the bin where it fits the tightest. In case there is no open bin to fit the current item, a new bin is created where the item is inserted.

Lastly, the First Fit Decreasing (FFD) places each item in the left-most bin as long as the bin's capacity is not exceeded. As shown in [21],

$$R_{BFD}^{\infty} = R_{FFD}^{\infty} = \frac{11}{9}.$$
 (4)

In combination with their online variants, these algorithms will be used as a reference to evaluate the performance of our Modified Any Fit algorithms in Sec. VI.

#### C. Conclusion

Although the temporal aspect of the Bin Packing Problem has already been reviewed, there is a gap when it comes to the possibility of rebalancing the items between the different bin instances. Existing solutions lack a deterministic metric to account for the rebalancing cost, and present conservative heuristic algorithms to migrate the items to different bins (items with higher cost are not migrated).

Also, in view of the fact that the existing approximation algorithms were developed to solve a single iteration of the BP problem, these have to be adapted to the problem at hand, which requires solving a new iteration given an already existing assignment of items to bins. Despite the fact that the adaptation presented in Section IV-C improves these algorithms' performance with respect to the rebalance cost, there is still room for improvement.

Therefore, since modeling the message broker consumption domain as a variable item size bin packing variant, is, to the best of our knowledge, a novel approach, in Section IV-A we provide with a metric (Rscore) that encodes the rebalance cost for a given iteration. Based on this metric, we contribute with four new heuristic algorithms that simultaneously aim to minimize the operational and migration costs (Section IV-B).

## III. PROBLEM FORMULATION

A group of consumers is interested in consuming data from several partitions/queues with varying load within the message broker. The set of partitions is distributed between the different consumers of the group to simultaneously parallelize and load-balance. Each partition can only be assigned a single consumer, whereas a consumer can be assigned several partitions. This problem is contained within the Data Consumption Domain of Figure 2.

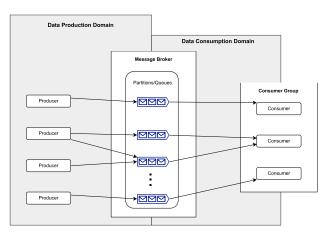


Fig. 2: Representation of data production and consumption domains within a message broker environment.

The aim of our work is to achieve a deterministic approach to determine the number of consumers required working in parallel, so as to guarantee that the rate of production into a partition is not higher than its rate of consumption by the consumer group. In contrast, if this were not the case, messages would accumulate leading to the lag between the last message inserted and the last message read by the consumer group to increase with time.

We assume that the maximum consumption rate of a single consumer is constant, and if there is enough data to be consumed, this is the speed the consumer functions at when working "full throttle". This is elaborated in Section VI based on several tests performed to determine this capacity value for a consumer.

Based on the previous information, the model for this pipeline fits the constraints of the Single Bin Size Bin Packing (SBSBP) variant, where the bins are consumers that have as capacity their maximum consumption rate, and the weights are the partitions and their respective write speeds. The problem then is to find the minimum amount of consumers where to fit all the partitions so as to make sure that the sum of the write speeds of the partitions assigned to a single consumer does not exceed its maximum capacity.

For a single iteration, the optimal solution finds the arrangement between the partitions and the consumers that minimizes the amount of instances, but this solution is not static, as the write speeds of the partitions changes with time. As such, there is a second factor to take into consideration which is the partition reassignment.

When a partition is reassigned, because two consumers from the same group cannot be consuming from the same partition at a time, when assigning a partition to another consumer, the one it is currently assigned to has to stop consuming in order to allow the new consumer to start. Due to this process, there is some downtime where data is not being consumed from a

For this reason, making use of an optimal algorithm that also minimizes partition redistribution, is not feasible as it

would not run within the necessary time requirements due to the NP-hard nature of the problem [22]. To determine the arrangement of partitions and consumers, this work is based on approximation algorithms. As is clear, there is no approximation algorithm which considers item redistribution.

Consequently, the BP problem is remodeled to take the time instant t at which the algorithm is to be executed into account.

$$\min \qquad \sum_{i \in B} y_i \tag{5}$$

subject to 
$$\sum_{j \in L}^{i \in B} \hat{w}_j(t) \cdot x_{ij} \le y_i \quad \forall i \in B$$

$$\sum_{i \in B} x_{ij} = 1, \qquad \forall j \in L$$
(7)

$$\sum_{i \in B} x_{ij} = 1, \qquad \forall j \in L$$
 (7)

$$y_i \in \{0, 1\}$$
  $\forall i \in B$  (8)  
$$x_{ij} \in \{0, 1\}$$
  $\forall i \in B, j \in L,$  (9)

$$x_{ij} \in \{0, 1\} \qquad \forall i \in B, j \in L, \quad (9)$$

where set B corresponds to the available bins, and L as the list of items to be arranged into different bins. Decision variable  $x_{ij}$  and  $y_i$ , indicate whether an item j is packed in the bin i, and whether bin i is used respectively. As for Constraints 6 and 7, the former assures that the sum of the items in a bin does not exceed it's capacity, and the latter makes sure that every item is assigned a bin.

Time instant t represents an instant at which a measurement was performed of the items' sizes, leading to a new computation of the bin packing assignment, and new values for  $x_{ij}$ 

Since an assignment represents a consumer reading data from a partition, an item can also be reassigned to another consumer (bin), if at time instant t there is already a consumer from the group reading data from it.

#### IV. ALGORITHM

#### A. Rscore

Within this problem's context, rebalancing inevitably implies having the consumer group stop consuming from a partition while it is being reassigned from one consumer to another. There cannot be a concurrent read from the same partition by members of the same group.

This paper introduces the Rscore metric to compute the total rebalance cost of a group's reconfiguration. The metric reflects the impact of stopping the data consumption from the partitions that are being rebalanced. As such, the Rscore computes the rate at which data accumulates, in consumer iterations per second.

In essence, the combination of the time it took to rebalance a set of partitions and the Rscore, encodes information as to the maximum number of consumer iterations required to fully recover the data that accumulated, while the set of partitions was being rebalanced.

Provided the data presented in Table I, the following Equation 10 presents  $R_i$ , the Rscore for iteration i.

$$R_i = \frac{1}{C} \sum_{p \in P_i} s(p) \tag{10}$$

TABLE I: Data required to compute the Rscore.

Notation	Description
$P_i$	Set of partitions rebalanced in iteration $i$
s(p)	Write speed of partition p
C	Maximum consumer capacity in bytes/s

#### B. Modified Any Fit

Any Fit algorithms focus on reducing the amount of bins used to pack a set of items, disregarding the cost associated with reassigning items. These need to be modified to include the rebalancing costs that affect the solution performance significantly. Algorithm 1 illustrates the implementation of the modified any fit that will be further described for the remainder of this section.

Given the current consumer group's state (the partitions assigned to each consumer), and a set of unassigned partitions, the modified algorithms differ from the decreasing versions of the Any fit algorithms described in Section II-B, wherein the former class of algorithms does not sort the set of items but, in turn the consumers of a consumer group based on their assignment.

There are two sorting strategies when sorting the group of consumers:

- Sorting consumers based on the cumulative speed of all partitions assigned to it (cumulative sort);
- Sorting consumers based on the partition assigned to it that has the biggest measured write speed (max partition sort).

After sorting the current consumer group using one of the above strategies, for each consumer in the sorted group, the partitions assigned are sorted based on their write speed. From smallest to biggest, each partition is inserted into one of the bins that have already been created for the next iteration's assignment (future assignment). The insertion is made based on one of the any fit strategies, which can either be the Best or Worst Fit strategy. If the insert is successful, the partition is removed from the sorted list of partitions. Otherwise, if there is no existing bin that can hold the partition, then the current consumer assigned to it is created.

The remaining partitions in the sorted list are inserted into the created bin (which is also the consumer they are currently assigned to), from biggest to smallest. If the partition is inserted successfully, it is removed from the list of partitions. If a partition does not fit into the newly created consumer, then the remaining partitions are added to the set of unassigned partitions.

After repeating this procedure for all consumers, there is now a set of partitions which have not been assigned to any of the consumers in the future assignment. The final stage involves first sorting the unassigned partitions in decreasing order (based on their measured write speed), and assigning each partition to consumer from the new consumer group according to a fit strategy.

TABLE II: Modified implementations of the any fit algorithms.

Algorithm	Consumer Sorting Strategy	
Modified Worst Fit (MWF)	Cumulative write speed	
Modified Best Fit (MBF)	Cumulative write speed	
Modified Worst Fit Partition	Max partition write speed	
(MWFP)		
Modified Best Fit Partition	Max partition write speed	
(MBFP)		

# Algorithm 1 Modified Any Fit Algorithm

```
Input: current consumer group configuration C &
    currently unassigned partitions U
Output: new consumer group configuration N
 1: N \leftarrow new ConsumerList with assign strategy
 2: S \leftarrow \text{sort } C on cumulative or max partition
 3: for c \in S do
       pset \leftarrow partitions assigned to c
 5:
       pset \leftarrow sort \ pset \ in \ decreasing \ order
 6:
       for i \leftarrow pset.size() - 1 to 0 do
 7:
         p \leftarrow pset[i]
         result \leftarrow N.assignOpenBin(p)
 8:
         if result = false then
 9:
            break
10:
         end if
11:
12:
         pset.remove(p)
       end for
13:
       if pset.size() = 0 then
14:
         continue
15:
16:
       end if
17:
       N.createConsumer(c)
       for p \in pset do
18:
         result \leftarrow N.assign(c, p)
19:
         if result = false then
20:
            break
21:
22:
         end if
23:
         pset.remove(p)
       end for
24:
       U.extend(pset)
26: end for
27: U \leftarrow \text{sort } U \text{ decreasing order}
28: for p \in U do
       N.assignBin(p)
30: end for
31: return N
```

# C. Approximation Algorithms Adaptation

Adding to the procedures described in Sec. II, another step was included in the approximation algorithms when creating a new bin that does not have an affect on the total number of bins used by these algorithms. If the consumer that is currently assigned to the partition has not yet been created in the future assignment, this is the bin that is created, otherwise, the lowest index bin that does not yet exist is the one created. This is not presented as a modification to the existing algorithms, it simply adapts these to the added rebalance concern.

#### V. KAFKA CONSUMER GROUP AUTOSCALER

There are three components that interact with one another to provide a fully dynamic pipeline capable of autoscaling based on the current load of data being produced to the partitions of interest, as presented in Fig. 3.

- The monitor process is responsible for measuring the write speed of each partition the group is interested in consuming data from, which is equivalent to specifying the size of the items of the bin packing problem.
- 2) This information is then delivered to the controller, which is responsible for managing a consumer group (creating and deleting consumer instances), and mapping each partition to a consumer.
- 3) The consumers are then informed of their tasks and read the data from the partitions that were assigned to them by the controller.

This system was applied in a real world context, with the goal of extracting data published to Kafka topics to be inserted into a Datalake, being a part of the Extraction domain of the ETL process.

#### A. Monitor

To solve the BP problem, initially, the controller requires as input the write speed of each partition the consumer group is interested in consuming data from. The monitor process is responsible for providing this information.

Kafka provides an Admin client, which can be used to administer the cluster and query information about it. This client/class exposes a method describeLogDirs() which queries the cluster for the amount of bytes each TopicPartition has. A TopicPartition is a string-integer pair, which identifies any partition (integer) within a topic (string).

Each time the admin client queries the partition size, a timestamp is appended to the measurement, and it is inserted into the back of a queue. Any query older than 30 seconds, which is guaranteed to be in the front of the queue, is removed. We use the average write speed over the last 30 seconds to estimate a single partition's write speed. We compute the difference between the first and last queue elements (i.e., the earliest and latest measurement of the partition size) regarding the last 30 seconds. We divide the result by that time amount to obtain our write speed estimate in bytes/s.

After computing the write speed for all the partitions of interest, the information has to be communicated to the controller/orchestrator. To benefit from an asynchronous approach, this monitor process communicates with the controller/orchestrator process via a Kafka topic illustrated in Fig. 3 as monitor .writeSpeed.

## B. Consumer

The Consumer goes through four important phases within its process to approximate its consumption rate to a constant value when being challenged to work at its peak performance. These phases repeat cyclically until the consumer is terminated by an external signal. Fig. 4 illustrates the consumer's process.

The consumer is configured with two important parameters,  $BATCH\_BYTES$  and  $WAIT\_TIME\_SECS$ , which indicate respectively, the amount of bytes the consumer waits to gather in a single iteration, and the amount of time it is allowed to wait to gather the information.

The first phase has the consumer attempt to fetch  $BATCH\_BYTES$  from the partitions it is consuming data from. After this condition is satisfied or  $WAIT\_TIME\_SECS$  is exceeded, the consumer moves on to the second phase. Here the consumer processes each individual record, and batches records that originated from the same topic together. There are different data lake tables for each topic, and therefore not all records are inserted into the same destination table.

The third phase is where the consumer sends the records into the data lake, performing an asynchronous request for each topic it fetched data from in the same iteration.

Having forwarded all the records into their respective data lake tables, the consumer then verifies its metadata queue to verify if there are any change in state messages to be consumed. This queue is how the Controller process (Sec. V-C) informs each consumer of their assignments. If there are new messages, the consumer reads all messages in the queue, and updates its state. Only after having successfully updated its state and persisted its metadata, does the consumer send an acknowledgment back to the Controller to indicate the successful change in state. This cycle repeats until the Controller removes the consumer from its group of active consumers.

# C. Controller

The controller is the system component responsible for orchestrating and managing the consumer group. The write rate of each partition computed by the monitor process is an input to the approximation algorithm that determines new consumer group configurations. Based on these configurations, the controller creates the consumers that do not yet exist, communicates changes in assignment to each consumer in the group, and deletes consumers that are not required in new computed group's states.

As shown in Fig. 3, there are two topics that function as communication intermediaries between the three system components. The topic illustrated by <code>monitor.writeSpeed</code> is where the controller reads the partitions' write speeds, whereas the topic illustrated by <code>consumer.metadata</code> is where the controller sends messages to each consumer to inform the change in their state. Regarding the latter Kafka topic, partition 0 is reserved for communication directed toward the controller, whereas the remaining partitions within <code>consumer.metadata</code> represent a one-to-one mapping to each consumer. Therefore, if the controller wants to communicate with consumer N, it sends a record into metadata partition N.

This communication architecture was devised to achieve an efficient communication model, defined as the amount of information that is relevant relative to the amount of data read.

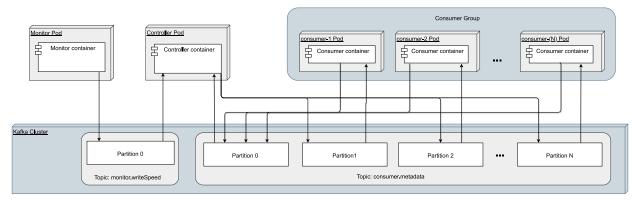


Fig. 3: System architecture.

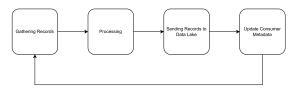


Fig. 4: Consumer Insert Cycle.

With this pattern, all the data read is relevant to the reading entity.

The controller can be summarized by a state machine, intended to continuously manage a group of consumers and their assignments, illustrated by Fig. 5.

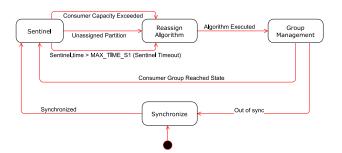


Fig. 5: Controller State Machine.

The Sentinel state has the controller read the information published by the monitor component to update its current consumer group's state, and determine whether it has to recompute the group's assignments. If it evaluates one of the exit conditions as true, the controller transitions into the Reassign Algorithm state. Then, it employs one of the approximation algorithms mentioned in Sections II-B and IV-B to solve the Bin Packing Problem heuristically.

The approximation algorithm outputs the desired state in which the controller wants its group of consumers. Hence, the first step within the Group Management state is to compute the difference between the current state of the group and the desired state. This difference encodes information regarding: the consumers to be created; the partitions each consumer has to stop consuming from; the partition each consumer has to

start consuming from; and lastly, the consumers that have no assignment, and therefore can be decommissioned.

The state difference allows the controller to operationalize the transition into the new state. Firstly, the controller creates the new consumer instances, which involves the controller communicating with a Kubernetes cluster to create the deployments related to each consumer. We chose to have different deployments for each consumer, so that the information related to which consumer.metadata partition the consumer had to read from, could be transmitted through the deployment's manifest metadata.name attribute. Secondly, the controller informs each consumer of their change in state by transmitting the start and stop consuming messages to each consumer via their respective consumer.metadata partition. It is important to note that communicating the state change is a synchronous process. This assures that while rebalancing partitions there at most one consumer from the group reading data from a partition. This means that for each partition being rebalanced, the controller first sends out the stop consuming message. Only after the consumer informs the controller of having acted upon the message, can the controller send out the start consuming record to the new consumer. After the consumers have reached their intended state, the controller shuts down the inactive consumers.

The Synchronize state is used to synchronize the consumer group's real state with the controller's perceived state. This is to guarantee the controller is capable of recovering from an unexpected termination, which can lead to an inconsistent perception of the consumer group's state.

#### VI. EXPERIMENTATION

## A. Test Data Generation

Throughout this section, we use the term measurement to represent a map of values that indicate the speed for each partition of interest. The term stream refers to a sequence of measurements in the form of a list. Each measurement of a stream simulates the items' sizes for an instance of the BP problem, which is an input for the approximation algorithms.

TABLE III: Data to generate a stream.

Symbol	Description
P	Set of partitions of interest for the consumer group.
$s_i(p)$	Speed for a partition $p \in P$ at an iteration $i$
$\phi(\delta)$	Uniform random function that selects a value between $[-\delta, \delta]$
C	Bin Capacity for the Bin Packing Problem.

To generate a stream of measurements, given N (the number of measurements desired) and  $\delta$  (maximum relative speed variation between two sequential iterations), at first the initial speed  $s_0(p)$ ,  $\forall p \in P$  has to be defined. Four different approaches were tested for the partition's initial value: choosing a random value between  $[0,100]\% \cdot C$ ; setting the initial speed of all partitions to 0; setting the initial speed of all partitions to  $50\% \cdot C$ ; setting the initial speed of all partitions to C. Given that there was no significant difference on the outcome with these variations, the results presented were obtained using the streams of data generated having an initial speed for all partitions that was randomly selected between  $[0,100]\% \cdot C$ .

Therefore, given  $s_0(p) \ \forall p \in P$ , the remaining measurements were obtained using:

$$s_{i}(p) = \max\{0, s_{i-1}(p) + \frac{\phi(\delta)}{100} \cdot C\},$$

$$\forall \ p \in P \ \land \ i \in \{1, 2, ..., N-1\}$$
(11)

Using the aforementioned procedure, 6 different streams of data were generated by setting N=500 and setting  $\delta$  to a value belonging to the set  $\{0,5,10,15,20,25\}$  for each stream of data ( $\delta$  does not change within a stream).

# B. Metrics

The metrics used to compare the performance between the algorithms are the Cardinal Bin Score  $(CBS_{\delta}(a))$  and the Average Rscore  $(E^a_{\delta}(R))$  over all iterations of each stream.

TABLE IV: Data to compute the cardinal bin score and the expected Rscore for a stream of measurements.

Symbol	Description
A	Set containing the existing and proposed approximation algo-
	rithms.
$z_i^{\delta}(a)$	number of bins used in iteration $i \in \{0, 1,, N-1\}$ of a
	stream defined by $\delta$ , by algorithm $a \in A$ .
$R_i^a$	Rescore for an iteration $i \in \{0, 1,, N-1\}$ for the outcome
	provided by algorithm $a \in A$ .

The cardinal bin score is calculated using the following expression:

$$CBS_{\delta}(a) = \frac{1}{N} \sum_{i=0}^{N-1} \frac{z_i^{\delta}(a) - min_{b \in A} \{ z_i^{\delta}(b) \}}{min_{b \in A} \{ z_i^{\delta}(b) \}},$$

$$\forall a \in A \land \delta \in \{0, 5, 10, 15, 20, 25 \}.$$
(12)

This metric expresses how many more bins, on average, an algorithm  $a \in A$  has compared to the algorithm that made use of the least bins, which encodes the operational cost. The lower this value, the better the algorithm performed for a given stream.

The expected value of the Rscore, is used to compare the rebalance cost for a single stream, and is computed as follows:

$$E_{\delta}^{a}(R) = \frac{1}{N} \sum_{i=0}^{N-1} R_{i}^{a},$$

$$\forall a \in A \land \delta \in \{0, 5, 10, 15, 20, 25\}.$$
(13)

The aim is also to minimize an algorithm's Average Rscore.

## C. Modified Any Fit Evaluation

Each algorithm was evaluated over a stream of measurements, persisting the Rscore and the number of bins used for each iteration. The algorithms are compared with respect to the same stream.

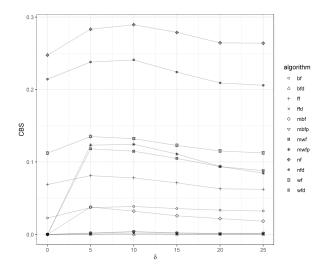


Fig. 6: Cardinal Bin Score (CBS) for all implemented algorithms.

When evaluating the Cardinal Bin Score, the worst performing algorithm, as shown in Fig. 6, is the next fit followed by its decreasing version. The remaining any fit decreasing algorithms, are the ones that perform the best, with the best fit decreasing consistently presenting the best results.

As for the modified versions of these algorithms, due to its sorting strategy, MBFP shows the best results. It is also worth noting that for smaller variabilities, the modified algorithms behave similarly to the online versions of their any fit strategy with respect to the CBS, since the partitions aren't necessarily assigned from biggest to smallest. On the other hand, the higher the delta, the bigger the variability, which also leads to more rebalancing, having the modified algorithms behave more like the decreasing versions of their fit strategy.

With regards to the Rscore, a common trend can be verified for all algorithms, where an algorithm's Average Rscore increases with the value of  $\delta$ , as can be seen in Fig. 8. This should be expected as the bigger the  $\delta$ , the more variability there is between the items' sizes in two consecutive measurements of a stream.

With respect to the average Rscore, the algorithms that perform the best are the Modified Any Fit algorithms and the

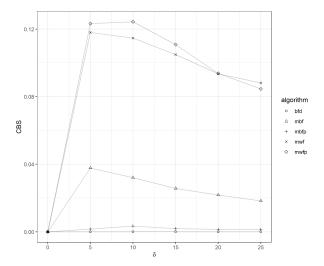


Fig. 7: Cardinal Bin Score (CBS) filtered to present the modified and the BFD algorithms.

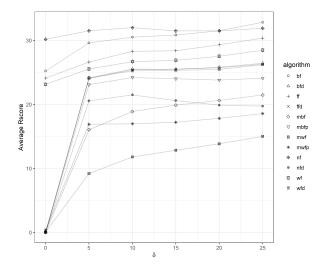


Fig. 8: Impact on Rscore for different Deltas (random initial partition speed).

NFD. The reason why the NFD appears within the five best algorithms, is due to the increased amount of bins required to pack the items into its bins. This is related to the modification made to the existing approximation algorithms, presented in Sec. IV-C. This modification leads to less rebalancing, as the partition might not have to be assigned a different bin than it is currently assigned, if new bin is created for it.

For a similar reason, the modified algorithms that perform the best with regards to the Rscore, are also the ones that perform worst (compared to the remaining modified algorithms) when evaluating the CBS. As such, on account of the added rebalance concern within the modified algorithms, these present an improvement when it comes to the rebalance cost compared to the existing approximation algorithms.

We find the pareto front, so as to determine the set of solutions that are most efficient, provided there are trade-

offs within a multi-objective optimization problem. Excluding MWFP, the modified algorithms are consistently a part of the pareto front, as shown in Fig. 9, which implies these are a competitive alternative when solving this variation of the BP problem.

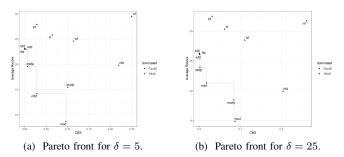


Fig. 9: Pareto front for different deltas comparing the Cardinal Bin Score and the Average Rscore.

#### D. Kafka Consumer Group Autoscaler Evaluation

The consumer group autoscaler, was developed as a proof of concept as to how this variation of the Bin Packing problem could be applied in a message broker environment. As such, we now present the results when running this system in Maersk's (HUUB) production message broker environment, with the compute resources summarized by Table V.

TABLE V: Infrastructure used for experimentation

Component	Cloud Platform	Resource Classification
Kafka Cluster (3 Nodes)	AWS	r5.xlarge
Kubernetes	GCP	GKE autopilot
Monitor	GCP	Kubernetes Deployment (GKE)
Controller	GCP	Kubernetes Deployment (GKE)
Consumer	GCP	As many Deployments as consumers in
Group		the group (GKE)

One of the first assumptions, was that this problem was a variation of the SBSBP problem, and therefore, the consumer should present a constant maximum capacity when challenged to work at peak performance. To obtain this value, the consumer was tested in three very disparate conditions, specified in Table VI, all requiring the consumer to be reading the data at its maximum consumption rate. Between each test, we varied: the average amount of bytes present in each partition; the number of destination tables in the data lake; and the number of partitions assigned to the consumer instance. Fig. 10 presents the results of having the consumer run in these conditions, and clearly shows a common mode for the maximum consumption rate, around 2.3 Mbytes/s.

### VII. CONCLUSIONS

The work introduces a deterministic approach to minimize the number of consumers required working in parallel, where message brokers are concerned. This minimizes operational

TABLE VI: Testing conditions to obtain consumer maximum throughput measure.

Test ID	Total Bytes	Average Bytes	Number of Partitions	Number of Tables
Test 1	648 Mbytes	20 Mbytes	32	1
Test 2	100 Mbytes	0.86~Mbytes	116	5
Test 3	678~Mbytes	4~Mbytes	144	5

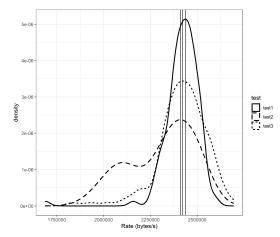


Fig. 10: Density Plot for the consumer's measured throughput in the three testing conditions.

costs. The approach assigns partitions to consumes guaranteeing that the rate of production into a set of partitions is not higher than the rate of consumption.

This study solves the consumer group autoscaling problem deterministically by analogizing the issue to a Bin Packing problem. The analogy corresponds item sizes to write speeds and bins to consumers. This paper also considers that write speeds can change over time, and assignments need to adapt to these changes. Reassignments pose a cost since they limit the consumers' capacity to read data. Terefore, we propose the Rscore to account for rebalancing costs.

To the best of our knowledge, there is no algorithm that accounts for the dynamic aspect of our BP problem. Hence, we propose four new BP-based heuristics that consider the re-scheduling costs (Rscore). Three of them are proven to be competitive solutions when solving the multi-objective optimization problem. Thus, the assignments they lead to have some robustness to future write speed changes.

Lastly, this paper challenges some of Kafka's core functionalities and provides tested alternatives which can be used as a foundation so as to improve the way in which a consumer's load is modeled, and the manner in which the load (partitions) is distributed between the elements of a consumer group. Ultimately, our approach solves a real-world problem regarding the sensor reads of a logistics company at lower operational costs than their previous non-functioning solution.

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