Haren: A Framework for Ad-Hoc Thread Scheduling Policies for Data Streaming Applications

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ABSTRACT

In modern Stream Processing Engines (SPEs), numerous diverse applications, which can differ in aspects such as cost, criticality or latency sensitivity, can co-exist in the same computing node. When these differences need to be considered to control the performance of each application, custom scheduling of operators to threads is of key importance (e.g., when a smart vehicle needs to ensure that safety-critical applications always have access to computational power, while other applications are given lower, variable priorities).

Many solutions have been proposed regarding schedulers that allocate threads to operators to optimize specific metrics (e.g., latency) but there is still lack of a tool that allows arbitrarily complex scheduling strategies to be seamlessly plugged on top of an SPE. We propose `Haren` to fill this gap. More specifically, we (1) formalize the thread scheduling problem in stream processing in a general way, allowing to define ad-hoc scheduling policies, (2) identify the bottlenecks and the opportunities of scheduling in stream processing, (3) distill a compact interface to connect `Haren` with SPEs, enabling rapid testing of various scheduling policies, (4) illustrate the usability of the framework by integrating it into an actual SPE and (5) provide a thorough evaluation. As we show, `Haren` makes it is possible to adapt the use of computational resources over time to meet the goals of a variety of scheduling policies.

CCS CONCEPTS

• **Information systems → Online analytical processing engines**; • **Software and its engineering → Scheduling**; *Middleware*.

KEYWORDS

Stream processing, Scheduling, Middleware

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1 INTRODUCTION

Data streaming is leveraged in applications dealing with heterogeneous data sources, variable input rates (and data distributions) as well as heterogeneous hardware (ranging from high-end servers to embedded edge devices). Stream Processing Engines (SPEs), the platforms running streaming *queries* (or simply queries), deploy the latter's operators to multiple SPE *instances* (i.e., processes) existing within or across multiple computational nodes. In this context, *resource scheduling* [3, 13, 27–29] chooses how and to which SPE instances to deploy queries' operators while *thread scheduling*, our focus, chooses how to allocate an SPE instance's threads to the operators deployed to it to meet specific performance goals.

Many related works have shown that custom thread scheduling (or simply scheduling) can reach better performance (e.g., lower processing latency) than that achieved when SPEs instantiate per-operator threads [7, 12, 24] which are scheduled by the Operating System (OS) [9]. Existing solutions discuss nonetheless specific scheduling policies (in combination with certain SPEs), without considering how to express the scheduling goals of a policy without the need to code its logic within an SPE.

This observation forms the basis of our work, which aims at identifying and generalizing the logic of a general scheduler that can encapsulate existing policies while decoupling its internals from those of an SPE. Thus, our research question is the following: *Is it possible to define an all-purpose SPE scheduling framework, which (i) allows the user to easily plug-in custom scheduling policies, (ii) transparently enforces those policies at runtime and (iii) requires minimal programming effort?* These requirements can be crucial, especially in large cyber-physical systems (such as smart grids and vehicular networks) in which users and analysts can continuously deploy applications of different criticality, priority or latency sensitivity [19, 23] and SPEs themselves can perform adaptive live reconfigurations (e.g., operator fusion and fission [11]) to adjust resources to query loads and costs. We provide an affirmative answer and present `Haren`, a general tool which can be used in combination with an SPE with minimal modifications. We evaluate it in combination with Liebre, a lightweight SPE for edge-computing [14]. In summary, we make the following contributions:

- We distill a compact set of primitives that can encapsulate the logic of the most common scheduling policies proposed in the literature, allowing users to define scheduling semantics without the need for altering the internals of the SPE.
- Together with these primitives, we define the facilities that the SPE needs to provide for custom scheduling to happen.
- We design and implement a framework that leverages such primitives in a lightweight fashion without dedicated threads but by sharing the job among threads running the analysis.

- We perform a thorough evaluation for different scheduling policies (of different complexity) leveraging hardware that can be employed at the edge of large cyber-physical systems, where custom scheduling policies are needed the most [19].

As we show, Haren allows the user to define rich scheduling policies (even multiple dedicated ones when not all queries in an SPE instance share the same performance goals) and enforces them with minimal overhead, achieving performance goals that are not matched when the SPE relies on the underlying OS scheduler.

Outline: § 2 covers preliminaries about data streaming and scheduling. § 3 presents our goals and system model. § 4 overviews Haren while § 5 and § 6 discuss its internals. § 7 presents our evaluation of Haren. Last, § 8 covers related work and § 9 concludes the paper.

2 PRELIMINARIES

Streams & Operators. A *stream* is an unbounded sequence of tuples sharing a schema composed by attributes $\langle a_1, \ldots, a_n \rangle$. A *query* is a DAG of *operators* connected by streams. External *data sources* generate tuples to be processed by the operators of the query. These tuples, which are referred to as *ingress tuples*, are delivered to queries by *Ingress operators* (also called *Sources* or *Spouts* [7, 12, 24]), are pushed through the rest of the operators of the query, possibly resulting in new tuples, and are eventually delivered as *egress tuples* to *Egress operators* (also called *Sinks* [7]), which forward them to users or other applications. Streaming operators define at least one input stream and one output stream. The only exceptions are Ingress, which has no input and a single output stream, and Egress, which has one input but no output streams. The output tuples of an operator that are waiting to be processed by another operator connected to it are maintained in a queue shared between the two.

Clock time attribute. We assume that, apart from the user-defined attributes, all tuples carry a *clock* time *ta* attribute[1]. This attribute carries the clock time at the moment in which the tuple is forwarded by the Data Source producing it[2]. If a tuple t is created by an operator of the query, its clock time is set to the respective value of the latest input tuple triggering the creation of t at the operator. By extension, each tuple t that is not an ingress tuple carries the clock time of the latest ingress tuple triggering its creation.

Sample Query. Figure 1 presents a sample query composed by two operators (plus one Ingress and one Egress). For each input tuple, operator op_1 creates an output tuple carrying the same *ta* attribute of the input tuple plus an attribute c for the sum of a and b. Operator op_2 produces tuples carrying, for each fixed *window* [2] of 10 minutes, the attribute *ta* of the latest tuple contributing to the window, the attribute d containing the maximum value of c observed in the window and the attribute w, to specify the start time of the window. The figure also shows the tuples currently present in each queue. Since attribute *ta* is set for each output tuple created by an operator to the value of the latest input tuple contributing to such output tuple, it can be observed that all the tuples in a queue of a particular operator have *ta* values that are smaller than or equal to those of the latter's input queues. We use in the remainder the terms *upstream* and *downstream* peers to refer to the operators preceding and following an operator, respectively (e.g., op_1 is the upstream peer of op_2 while op_2 is the downstream peer of op_1).

Scheduling. An SPE instance running a set of operators (from one or more queries) has access to one or more CPU cores (mapped to hardware threads). In our work, *scheduling* refers to the process of periodically deciding which operators (possibly of different queries) should be run and in which order, within an SPE instance. A scheduled operator runs its code inside a hardware thread. At any moment, an operator can be run by at most one thread.

A challenge in scheduling streaming operators is that, because of the varying rates and data distribution of data sources (which in turn affect the rates, data distribution and behavior of the queries' operators), scheduling policies cannot be defined statically at compile time, but need to be continuously refined over time.

The goal of custom scheduling for SPE instances is to control the performance characteristics of the queries. We quantify the performance of one or multiple queries as follows. Starting from the operator level, we quantify its performance over a period of time with the following metrics:

(1) *Throughput*, the number of tuples processed by the operator.
(2) *Latency*, the average clock time elapsed in between the operator's processing of each tuple t and t's clock time (i.e., the clock time of the latest ingress tuple triggering the production of t).
(3) *CPU Utilization*, the average CPU utilization (%) of the operator.
(4) *Memory Cost*, the maximum amount of memory consumed by the tuples maintained in the operator's input queues.

Extending the performance characterization from operators to whole queries, we define (i) the *query throughput* as the average throughput of the query's Ingress operators, (ii) the *mean* and *max query latency* as the average and maximum latency observed at its Egress operators, respectively, (iii) the *CPU utilization* as the sum of the CPU utilization of the query's operators, and (iv) the *memory cost* as the sum of the memory costs of all the operators of the query. These definitions can be extended to multiple queries by means of the sums, averages, and maximums of all their operators.

It should be noticed that these performance metrics depend on multiple aspects such as (i) the scheduling decisions, (ii) the arrival pattern of the incoming data, as well as (iii) the data distribution of the input values. For example, both the throughput as well as the memory cost depend on the CPU time allocated for a certain operator as well as the rate of the data source(s).

With respect to the example of Figure 1, one can observe that (i) given the tuples currently stored in the operators' queues and (ii) assuming that the next scheduled operator can process all its shown input tuples, the scheduling choice would depend on the desired performance metric. More concretely, scheduling the Egress operator would minimize the query's latency, scheduling operator op_1 would minimize the overall memory used while scheduling the Ingress operator would maximize the query's throughput.

3 GOALS AND SYSTEM MODEL

We aim at designing and implementing a general purpose scheduling framework that allows users to define ad-hoc scheduling policies. More concretely, we want to allocate the threads of an SPE instance in a streaming-application-aware fashion that can meet

[1] Clock time is sometimes referred to as *arrival time* in the literature [6]. If the data source is generating (and not replaying) the data, clock time is equal to *event time* [2].
[2] We assume that clocks of Data Sources and the processing node are synchronized with a time synchronization protocol such as NTP.

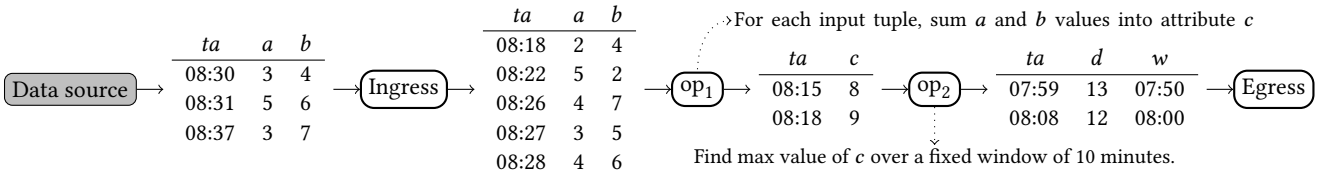


Figure 1: Sample query composed by two operators (plus one Ingress and one Egress) that sums the values carried by each tuple and then computes the max for such sum over a fixed window of 10 minutes.

complementary and richer performance goals than those enabled by the OS itself. Hence, we focus our study on a thread scheduling framework and assume that one or more query operators are deployed to a single SPE instance, where Haren also runs.

Our goal is to shape Haren as a component (accessible to both the user and the SPE) that sits in-between the OS and the SPE. On the one hand, Haren should expose an interface that allows users to deploy queries and define scheduling policies, as well as SPEs themselves to perform adaptive runtime reconfigurations (e.g., operator fusion or fission [11]). At the same time, Haren should also orchestrate the execution of the SPE and retrieve over time any information needed from the SPE to enforce the user-defined scheduling policies. In summary, Haren's aims at:

- G1 Distilling a compact interface for a scheduling middleware that can implement user-defined scheduling policies that optimize performance metrics agnostic to the OS (e.g., throughput, latency or memory utilization, among others).
- G2 Allowing the implementation of custom, user-defined rules for both *inter-thread scheduling* (i.e., specifying the assignment of operators to threads) and *intra-thread scheduling* (i.e., specifying the scheduling of operators within each thread).
- G3 Distributing and sharing scheduling overheads among available physical threads to take advantage of multi-core nodes.

3.1 System model

Tuples, operators, and queries have various *features* that characterize their behavior and state. A general-purpose scheduling framework must be aware of the changing nature of these features to make informed decisions and orchestrate the execution of queries' operators according to a user-defined scheduling policy.

Not all features are equal in terms of how they change and in terms of how their changes can be observed. A first distinction can be made between *static* features (e.g., the type of an operator) and *dynamic* ones (e.g., the selectivity of an operator, which depends among other things on the data being fed to it). A second distinction can be made between features that are immediately derived from an operator (e.g., its number of input streams) and features that are derived from the input/output queues of an operator and/or the tuples maintained in such queues (e.g., the clock time of the earliest tuple maintained in any of the operator's input queues). This second distinction is crucial because it results in two critical observations. First, certain features can change over time independently of whether the operator is scheduled or not. This is the case, for instance, for the earliest clock time of any tuple in the input queues of an operator, given that it could change if any of its upstream operators are scheduled. Second, it might not be possible to update particular features of some operators unless these operators are executed (e.g., the average time needed by an operator to process one tuple, also referred to as the cost of an operator). Based on these observations, we introduce the following definitions.

ID	Feature	Type
c	Cost	Dynamic, independent, execution-intrinsic
s	Selectivity	Dynamic (except for Egress operators), independent, execution-intrinsic
l_H	Head clock time	Dynamic, dependent on upstream and downstream peers, execution-intrinsic for Ingress operators

Table 1: Table of features considered in the paper.

Definition 3.1. A feature F of operator op_i is *independent* if it can change only upon execution of op_i.

Definition 3.2. An operator op_i is *feature-depended* on operator op_j for feature F if F for op_i can change upon execution of op_j.

Definition 3.3. A feature F of operator op_i is *dependent* if it can change upon execution of op_i as well as operators on which op_i is feature-dependent.

Definition 3.4. A feature F of operator op_i is *execution-intrinsic* if it can be updated only upon execution of op_i.

Since operators, queues and tuples are accessed by the SPE, we assume the latter provides an interface (such as a metrics system [7, 12]) for Haren to retrieve up-to-date feature values. Although the features used by Haren can be arbitrarily complex, to keep the discussion tractable, we will focus on a specific set of them. These features, presented in Table 1, are required to implement most of the scheduling policies proposed in the literature, including the policies we later use in our evaluation. The table displays features along with their abbreviated id and type. For brevity, we do not include static features that can be trivially computed, such as the operator type. As aforementioned, the *cost* is the average time spent by an operator to process a single input tuple. The *selectivity* defines the average number of output tuples produced per processed input tuple. Observe that it can be higher than 1 for operators that generate multiple output tuples for every input tuple (e.g., an operator that splits a sentence into words). Cost and selectivity are used in many scheduling policies, to optimize for different metrics

such as the average latency or the memory cost of the queries [23]. The *head clock time* is the earliest clock time of the tuples at the head of the input streams of an operator. This feature is also used in various scheduling policies (e.g., to optimize the maximum latency of a query based on its operators head latency, which is derived from their head clock time [6]).

We assume in the remainder that the SPE instance has K active CPU cores which correspond to hardware *Processing Threads (PTs)*. We refer to the i-th processing thread as $PT_i \mid i \in \{1, \ldots, K\}$ and to the i-th operator of the j-th query as op_i^j (but omit the query number if it is not essential for the discussion).

4 OVERVIEW

Streaming applications have a live and changing nature, with varying input stream rates and data distributions. In order to correctly enforce a scheduling policy, features and priorities that change over time need to be periodically updated. Since changes in features can depend on scheduling decisions (see § 3), information about scheduling decisions must also be collected over time.

Figure 2 shows the two main *tasks* executed by Haren's PTs, namely execution (T_E) and scheduling (T_S). PTs run task T_E during the majority of the time and switch periodically to task T_S. These tasks isolate the portions of time during which scheduling information is gathered for priority updates (i.e., when PTs must synchronize) from those during which PTs can be dedicated to running the operators deployed to the SPE instance. The separate tasks give fine-grained control over the scheduling overhead, which is proportional to the time spent gathering information about scheduled operators and updating features and priorities.

As stated in § 3, we aim at distributing and sharing the scheduling overhead among all PTs (Goal G3). Because of this, Haren parallelizes the costly parts of T_S and lets all PTs (in a random fashion) take care of the portions of T_S that can be run more efficiently in a sequential fashion. We overview in the following tasks T_E and T_S and refer the reader to § 5 and § 6 for more detailed descriptions.

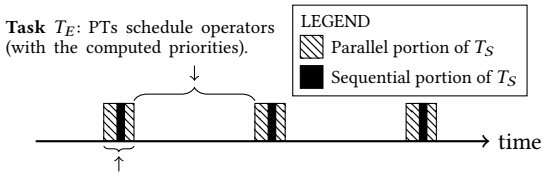


Figure 2: Alternation of T_E (execution task) and T_S (scheduling task) during the runtime execution of Haren.

Overview of T_E. During this task, each PT locally executes the operators that were assigned to it, keeping track of the executed operators, in order to share this information during the following T_S. To make certain that fresh values of the operators' features are available, PTs also ensure that operators with execution-intrinsic features do not stay unscheduled for an excessive period of time.

Overview of T_S. During this task, PTs update the scheduling decisions by sharing information about the operators scheduled during the previous T_E. In § 3, we distinguished features into independent and dependent (Definition 3.1 and Definition 3.3). Although it is easy for a PT to detect if an independent feature of its operators needs to be updated, the same is not true for dependent features, because such features might depend on the actions of multiple PTs. Haren reduces overheads by defining a sequential portion of T_S in which exactly one PT (chosen randomly) updates all the dependent features that have potentially changed and, subsequently, redistributes the operators to all PTs. Then, each PT, in parallel, computes priorities for its operators and sorts these operators based on the recently updated priorities, concluding T_S.

Note that an operator might be assigned to different PTs in distinct executions of T_S. To prevent situations where two PTs try to execute the same operator at the same time (see § 2), the sequential portion of T_S also acts as a *barrier* that marks, for all PTs, the end of the current T_E and the beginning of the next. For the same reason, no operator is executed during T_S.

4.1 Inter-thread and intra-thread scheduling

Since SPE instances can run on multiple threads, Haren allows users to specify how to (i) assign operators to PTs and (ii) decide the order with which each PT should schedule the operators assigned to it. It does this by means of an *inter-thread* scheduling function (f) and an *intra-thread* scheduling function (g). F being the set of available features and O the set of operators deployed to the SPE instance, we define these functions as follows.

The *inter-thread scheduling function* $f : R^{|F|\times|O|} \rightarrow \{1, \ldots, K\}$ identifies which PT should execute which operator, for all the operators deployed to the SPE instance. Note that, when computing which PT should be in charge of executing a certain operator, the features of all the operators deployed to the SPE instance are given as input to f. Thus, f can be used to implement both simple thread assignment policies (e.g., assign the operators of queries to PTs in a round-robin fashion), as well as much more complex ones (e.g., assign operators so that the load is equal for all the PTs).

The *intra-thread scheduling function* $g : R^{|F|\times|O|} \rightarrow R^D$ maps the features of operator op_i to a D-dimensional *priority vector* $P_i = \langle p_{i1}, p_{i2}, \ldots, p_{iD} \rangle$. Also in this case, the features of all operators deployed to the SPE instance are input to g when computing the priority of each operator. Each element of the priority vector reflects a priority dimension. The execution of operators is prioritized based on a lexicographic sorting of their priority vectors. For example, a possible priority vector might describe two dimensions ⟨queryClass, cost⟩ (each computed based on the operators' features). In this case, operators with higher queryClass would be scheduled before others with lower queryClass, while operators with equal queryClass would be scheduled according to their cost.

4.2 Architecture

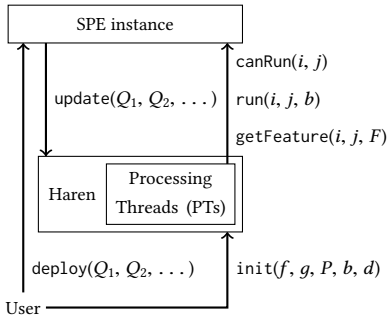
Figure 3 shows the APIs coupling an SPE instance with Haren, used by the latter to schedule the operators deployed to the former.

The user interested in running a set of operators belonging to queries $Q_1, Q_2, \ldots$ with a particular scheduling policy can invoke

the SPE's deploy function[3] and pass the queries' operators to be executed. She also initializes Haren with the inter-thread and the intra-thread scheduling functions f and g and the runtime parameters P, b and d (described in the figure). For simplicity and without loss of generality, the figure and our following discussion focus on a single SPE instance. When the queries' operators are deployed to either one or multiple SPE instances (see § 1), each SPE instance is coupled with one instance of Haren. The SPE instance notifies the associated Haren instance of the new deployment by calling update. Internally, Haren inspects the queries in order to identify the set O of operators to be scheduled (and their interconnections) at the coupled SPE instance. Once Haren identifies the set F of features used by f and g, Haren's PTs schedule the execution of the operators. This is done by invoking:

- SPE.canRun(i, j), to check whether operator op_i^j can be executed (i.e., if it has input tuples and space to place potential results in its output streams' queues).
- SPE.run(i, j, b), to run op_i^j, specifying b as the maximum number of tuples it can process during the function invocation (we refer to § 5 for more details about the role of b in scheduling).
- SPE.getFeature(i, j, F), to retrieve feature F for op_i^j.

The SPE instance can also invoke the function update when, due to runtime reconfigurations (e.g., operator fusion or fission [11]), the list of operators scheduled by Haren changes.



Haren input parameters

f	Inter-thread scheduling function.
g	Intra-thread scheduling function.
P	Scheduling period (interval between T_S invocations).
b	Maximum number of tuples an operator is allowed to process at every invocation.
d	Maximum amount of time an operator that has execution-intrinsic features used by f or g can stay non-scheduled.

Figure 3: APIs coupling Haren, the user and the SPE instance.

5 EXECUTION TASK (T_E)

In this section, we provide a detailed description of the actions performed by PTs during T_E. More concretely, we discuss (i) how each PT chooses the next operator to run, (ii) how it backs-off if there is no operator to be scheduled, and (iii) how it takes care of running operators for which execution-intrinsic features (Definition 3.4) have not been updated for more than the user-defined d time units.

The different variables accessed by each PT are presented in Table 2 while the main loop is shown in Algorithm 1. List $\mathbb{A}$ contains the operators assigned to each PT at the end of the previous T_S task. Before the first execution of T_S, all operators are given the same priority and assigned randomly to PTs. This also applies for operators added, removed or changed at runtime due to adaptive reconfigurations triggered by SPE instances (their assignment to threads and priorities are then updated during the first T_S following the reconfiguration).

Each PT traverses $\mathbb{A}$ until it finds the operator with the highest priority that can run, or until it reaches the end of $\mathbb{A}$ (lines 5-13). Here, we remind the reader that an operator can generally run (i) if

[3]For simplicity, Figure 3 depicts the user directly invoking the SPE instance's deploy function. In reality, she might do so indirectly, through an intermediate component such as a resource scheduler.

Algorithm 1: Main loop of PT – T_E

```
1  t_γ ← now()
2  while true do
3      op* ← ∅
4      run ← false
5      for op_i^j ∈ 𝔸 do
6          if (op* ≠ ∅ ∧ g(op*) > g(op_i^j)) ∨ (now() - t_γ > P) then
7              break
8          if SPE.canRun(i, j) then
9              SPE.run(i, j, b)
10             𝕃𝕌_i ← time()
11             𝔼 ← 𝔼 ∪ op_i^j
12             run ← true
13             op* = op_i^j
14     if not run then
15         backoff()
16     if now() - t_γ > P then
           // PT enters T_S
17         Haren.update() // Algorithm 2
           // PT leaves T_S
18         t_γ ← now()
           // Run delayed operators
19         for op_i^j ∈ 𝔸 do
20             if t_γ − 𝕃𝕌_i > d then
21                 SPE.run(i, j, b)
22                 𝕃𝕌_i ← time()
23                 𝔼 ← 𝔼 ∪ op_i^j
```

ID	Description
Thread-local variables	
$\mathbb{A}$	List with the operators assigned to the PT.
$\mathbb{E}$	Set that contains the operators that were executed by the PT at least once during the last T_E.
Shared variables	
$\mathbb{LU}$	Array of size $\|O\|$. $\mathbb{LU}_i$ is the latest timestamp when an operator was executed.

Table 2: Variables used during T_E.

it has tuples in its input queues as well as (ii) free space in its output queues (function SPE.canRun, line 9). If such an operator is found, it is executed and allowed to process at most b tuples, where b is one of the user-defined parameters (§ 4.2) which we refer to as *batch size*. Subsequently, the next operator in $\mathbb{A}$ is scheduled only if (i) it has the same priority of the previously run operator (and it can run)[4] and (ii) if the elapsed time is less than the scheduling period P. Intuitively, b is defined to limit the execution time of a given operator, allowing other operators to be scheduled too. Although Haren does not interrupt operators during the processing of a tuple, it can enforce preemptive scheduling policies, with the batch size b defining the preemption granularity. Smaller values of b allow for more frequent preemption of the scheduled operators, at the price of higher context-switching overhead.

If the PT reaches the end of the operator list $\mathbb{A}$ and does not find any operator that can run, it invokes a back-off function to avoid spinning (lines 14-15). PTs sleep using a simple exponential back-off algorithm. More specifically, they start with a very small sleep duration and double it at every invocation. The back-off time never exceeds the remaining duration of T_E and is reset every time a PT enters this task. Afterward (line 16), the PT checks if the time spent in the loop has surpassed the user-defined scheduling period P and if so, it enters T_S (line 17, later described in § 6).

As discussed in § 4, if any execution-intrinsic feature of operator op_i^j is used by f and g, Haren needs to run op_i^j if the latter has not been scheduled for more than d time units in order (i) for its feature to be up-to-date, and (ii) for the scheduling policies to be enforced correctly. Because of this, PTs record the last execution time for each operator they schedule (line 10). Moreover, when task T_S is completed, each PT checks if there are any operators in $\mathbb{A}$ that have not been scheduled for more than d time units and runs them if that is the case (lines 19-23). Lastly, observe that when PTs run an operator, they also add that operator to their set of executed operators $\mathbb{E}$ (lines 11, 23). This allows PTs to selectively update only features of specific operators during the next T_S task, based on the ones executed during T_E, as described in the following section.

6 SCHEDULING TASK (T_S)

The purpose of the scheduling task is to produce, for each PT, a list $\mathbb{A}$ of operators sorted by their priority vectors $P_i = \langle p_{i1}, p_{i2}, \ldots, p_{iD} \rangle$. This list of operators will then be used by each PT during the following T_E to pick operators for execution.

As mentioned in § 4, Haren tries to minimize the scheduling overhead by parallelizing the costly steps of this task and splitting the work between all PTs. However, as we discussed before (and further elaborate in this section), T_S also defines a sequential portion executed by exactly one (randomly selected) PT, which we denote as t^*. The sequential portion acts as a logical meeting point for PTs to synchronize their parallel work. In particular, the mechanics of T_S can be broken down into four main steps:

(1) Computing the up-to-date features, done partly in parallel (for independent features) and partly sequentially by t^* (for dependent features).

[4]The actual implementation does not invoke g but uses the priority value computed during the previous T_S. In the algorithm g is used for compact notation.

ID	Description
Global constants	
F	Set of all the features used by the user-defined scheduling functions f and g.
F_D	Set of dependent features.
F_C	Set of constant features.
D	Number of dimensions of the scheduling function g.
K	Number of PTs
PT	Array of dimension K, of all the available PTs.
Thread-local variables	
$\mathbb{P}$	Matrix of size $\lvert O\rvert \times D$ that has a row per operator in $\mathbb{A}$ and a column for each dimension of the intra-thread scheduling function g. Each entry (i, j) contains the priority value of the operator with index i for priority dimension j.
Shared variables	
O	Array of all the operators deployed to the SPE instance.
$\mathbb{F}$	Matrix of size $\lvert O\rvert \times \lvert F\rvert$ that has a row per operator in O and a column for each feature in F. Each entry (i, j) of the matrix contains the latest reported value of feature with index j for operator with index i.
$\mathbb{D}$	Bitmap of size $\lvert O\rvert \times \lvert O\rvert$ where $\mathbb{D}_{i,j}$ is 1 if, based on the user-defined priority function, running the i-th operator implies that the features of the j-th operator should also be updated. Statically filled in at the beginning. Diagonal full of 1s.
$\mathbb{U}$	Bit array of length $\lvert O\rvert$. $\mathbb{U}_i$ is 1 if the dependent features of operator i need to be updated.
t^*	The PT that runs the sequential part of T_S.

Table 3: Additional variables used during T_S.

(2) Assigning operators to PTs using the inter-thread scheduling function f, done sequentially by t^*.
(3) Updating the priority vectors P_i using the intra-thread scheduling function g, done in parallel by all PTs.
(4) Sorting the operators based on their priority vectors P_i, done in parallel by all PTs.

In the following, we discuss the challenges of the above steps and outline Haren's solutions to each one. All the new variables related to this task are presented in Table 3.

Updating the features. To begin with, this step is needed in order for Haren to compute the new priorities of the operators, since for the latter it needs to access the latest values of those operators' features. As previously discussed in § 3, these features can differ in *how frequently* they change, with some of them being static and others dynamic. Moreover, features can differ on *how* they change, with some being independent or dependent and execution-intrinsic or not execution-intrinsic. This heterogeneity of the features presents an opportunity to reduce the cost of the feature update. More specifically, Haren tries to *selectively update* only the values of (operator, feature) combinations which can have potentially changed since the last T_S. In order to facilitate such selective updates and improve performance, Haren stores, for every operator, the latest feature values it has retrieved in an $\lvert O\rvert \times F$ matrix denoted by $\mathbb{F}$, shared between PTs. When PTs execute T_S, they use their knowledge about possible feature dependencies to only update (operator, feature)

Algorithm 2: `Haren.update()` – T_S (Parallel Steps)

```
   // Update independent features
1  for op_i^j ∈ 𝔼 do
2      𝔽_i ← SPE.getFeatures(i, j, F − F_D − F_C)
3      𝕌_i ← 1
4      for op_k^j ∈ O | 𝔻_{i,k} = 1 do
           // Mark feature-dependent ops for update
5          𝕌_k ← 1
6  Haren.coordinate() // Algorithm 3
   // Compute priorities
7  for op_i^j ∈ 𝔸 do
8      ℙ_i ← g(i, j, 𝔽)
   // Sort based on priorities
9  sortOperators(𝔸, ℙ)
```

combinations whose value can have potentially changed. Updating features is a two-step process, the first executed in parallel by all PTs and the second executed sequentially by one PT at each T_S.

Independent Features. In this first part of the feature update, each PT updates the independent features of each operator in its (local) set of executed operators, $\mathbb{E}$. This step is shown in Algorithm 2 (line 2). Updating independent features can be done safely in parallel. This is because the values of an operator's independent features can change only if that operator is scheduled by the PT responsible for it. Since no scheduling of operators happens during T_S, `Haren` can be certain that any update to an independent feature of any operator will be final (for this T_S).

Dependent Features. As discussed in § 4, dependent features might change based on the scheduling decisions of more than one PT. `Haren` avoids concurrent attempts to update the value of the same feature for the same operator by multiple PTs, since deciding on a correct ordering of these concurrent updates would require the use of a synchronization protocol and thus add overhead to the system (e.g., `SPE.getFeature()` would need to return the value of the feature and the timestamp of its invocation atomically). At the same time, PTs would waste CPU cycles, since all updates to the same position of $\mathbb{F}$, except the last one, would be replaced. For these reasons, the second step of updating the features in `Haren` is done sequentially by t^*. This procedure is shown in Algorithm 3, lines 3-5. t^* decides which operators need to have their dependent features updated, using the shared bit array $\mathbb{U}$. This array is initialized during the previous, parallel step, with each PT marking (i) the operators they executed (Algorithm 2, line 3), as well as (ii) the feature-dependent operators of the executed operators (lines 4-5). For (ii), each PT needs to know which operator(s) are feature-dependent on each operator they executed. This knowledge is encoded in bitmap $\mathbb{D}$, which is initialized once, at the beginning of the execution, based on the structure of the streaming queries and the dependent features used in the scheduling policy. For this phase to work correctly, all updates to $\mathbb{U}$ by PTs must have finished and be visible to t^*. To ensure this, PTs are forced to wait at the `entryBarrier` (Algorithm 3, line 1) before the update of the dependent features can begin. When all PTs arrive at that barrier, they are allowed to pass it, and immediately afterward, all PTs, except t^*, are blocked at the `exitBarrier` (line 11). The PTs will wait there until the dependent features have been updated by t^*. The need for the second barrier is explained in the next paragraph. Since the only requirement for choosing a PT to become t^* is that there can be only one at every T_S, the PT is chosen arbitrarily: the last PT that leaves the `entryBarrier` is appointed to be t^* (line 2).

Algorithm 3: `Haren.coordinate()` – T_S (Coordination Step)

```
1  entryBarrier.await()
2  if last then
       // Start sequential (only t* enters)
       // Update dependent features
3      for op_i^j ∈ O | 𝕌_i = 1 do
4          𝔽_i ← SPE.getFeatures(i, j, F_D)
5          𝕌_i ← 0
       // Inter-thread scheduling
6      for op_i^j ∈ O do
7          t ← f(i, j, 𝔽)
8          𝔸_t.append(op)
       // End sequential
9      exitBarrier.await()
10 else
11     exitBarrier.await()
```

Assigning operators to PTs. After the features have been updated, t^* assigns operators to PTs, using the inter-thread scheduling function f, as seen in Algorithm 3 lines 6-8. Care is needed in this step so that the updated mapping of operators to PTs takes effect at the same time for all PTs. This ensures that `Haren` avoids situations where, for example, the same operator (which could be mapped to two distinct PTs in two distinct T_E) is executed concurrently by two different PTs. Such situations are avoided having all PTs except one block at `exitBarrier` (introduced above). Only when t^* has finished its work (and has called `await()` at the barrier), can all PTs move forward to update the priorities. If a reconfiguration was triggered by the SPE during the previous T_E, `Haren`'s data structures will be resized during this step, and any new operators will be randomly assigned to PTs. After the operator assignment, the two final parts of T_S, namely the calculation of the new priority vectors and the sorting of operators, are done in parallel by all PTs.

Priority Update. As discussed in § 4.1, the intra-thread scheduling function g can use features of any deployed operator to compute the priority vector $P_i = \langle p_{i1}, p_{i2}, \ldots, p_{iD} \rangle$ of operator op_i. To maintain simplicity without sacrificing performance, `Haren` performs the feature and priority updates separately, but executes them both in parallel in all PTs. To do the priority update, each PT applies the intra-thread scheduling function g to all operators in its operator list $\mathbb{A}$ (Algorithm 2, lines 7-8). This process begins immediately after the assignment of operators to PTs. The resulting priority vectors are stored in a thread-local $|O| \times D$ matrix denoted by $\mathbb{P}$.

Note that many of the priority functions in the literature can be defined recursively, i.e., the value of the function for an operator can depend on its respective value for other operators. Haren is optimized for such cases by taking advantage of the dependencies in the query DAG to update the priorities in an efficient order.

Sorting. After a PT has updated the priorities of all operators in $\mathbb{A}$, the only task that remains before PTs can enter T_E is to sort these operators by their priority. Thus, sorting is the final step of T_S, which once again is done in parallel by all PTs (Algorithm 2, line 9). The operators in $\mathbb{A}$ are lexicographically sorted according to the values of their priority vectors. More precisely, an operator op_m is considered to have higher priority than op_n if

$$(\forall k < l : p_{mk} = p_{nk}) \wedge (p_{ml} > p_{nl})$$

After the sorting is complete, each PT can immediately enter T_E without the need to synchronize with the other PTs.

7 EVALUATION

We evaluate Haren by integrating it with a real-world SPE, implementing several scheduling policies of different complexities and studying their behavior and performance. We utilize small, low-end devices usually found at the edge of cyber-physical systems. We chose them because, while Haren can provide custom scheduling facilities to SPEs running in any kind of computational node, scheduling decisions can have a higher impact on performance when processing resources are limited. We first describe the experimental setup, then cover the various scheduling policies we use and present results for different complexities of the latter.

7.1 Experiments setup

Hardware/software. We use Odroid-XU4 [17] devices (or simply Odroid) with Samsung Exynos5422 Cortex-A15 2Ghz and Cortex-A7 Octa core CPUs and 2 GB of RAM, running Ubuntu 18.04.2 LTS and Java HotSpot(TM) Client VM 1.8.0_201-b09. Haren's PTs run on the four big cores (i.e., K = 4). CPU consumption is measured with ps and memory usage is retrieved from the JVM Runtime.

Haren *Implementation.* We evaluate a fully-featured version of Haren, implemented in Java, and integrated with Liebre, a lightweight SPE for edge-computing [14]. The integration builds on Haren's API (§ 4) with few changes in the SPE's implementation.

Queries. We evaluate Haren using synthetic queries, each consisting of a chain of operators with custom cost and selectivity (see Table 1). The source data is artificially generated. Each chain has one Ingress operator that retrieves data from a Data Source, which runs independently of the SPE. All chains have the same length L. The selectivity and cost values of operators are chosen using a strategy inspired by [23]. More specifically, selectivity and cost are chosen at two levels: query-level and operator-level. Regarding *selectivity*, each query j is assigned a selectivity value s^j, which expresses the number of egress tuples produced for every ingress tuple, chosen uniformly at random from $[0.01, 1]$. Then, to satisfy the query selectivity, each operator of the query gets a selectivity equal to $e^{logs^j/L} \pm 10\%$. For the *cost* selection, each query j is assigned a cost class $z \in [0, 4]$ and then the query's cost is computed as $c^j = B \times 2^z$. The cost of a query is proportional to the minimum time required for an ingress tuple to be processed by all query's operators. The cost of the operators is then set to $c^j \pm 10\%$. B is the *base cost* parameter that allows us to vary the load and thus the utilization of the system. We use operator chains in our evaluation to stress-test Haren in a tractable manner by simulating an SPE with a heterogeneous load. However, it should be noted that Haren's model can handle complex query graphs that contain forks or joins, without any alteration. The correct handling of such cases depends only on the implementation of scheduling functions f and g.

7.2 Scheduling Policies

As described in § 1, Haren is a general scheduling framework that can implement most scheduling policies defined in the literature. To give evidence of this, we evaluate three scheduling policies from the literature, each of which optimizes a different performance metric. We also study a custom policy that we define in § 7.4. Apart from these policies, we also evaluate the performance when the SPE runs without Haren, executing each operator in a dedicated thread instead. An overview of the features, dimensions and goals of each policy is given in the following (discussing how they define function g) and also in Table 4. In all experiments, the inter-thread scheduling function f randomly distributes operators to all PTs. The queries are chains of operators with $L = 12$. The scheduling period P is 100ms and the batch size b is 10 tuples. Each experiment runs for at least five minutes and is repeated at least five times.

Dedicated Threads (OS), the baseline policy, is the default for many SPEs. Haren is not used and, instead, each operator runs in a dedicated thread. Threads are thus scheduled by the OS. Since the OS is agnostic to specific streaming-related metrics, the metric this policy optimizes depends on the OS scheduler.

First-Come-First-Serve (FCFS) has been shown to optimize the maximum latency of the queries [6]. Our implementation uses the inverse of the head clock time l_H (defined in § 3) as the operator priority. To minimize the maximum latency of the system, operators with higher head latency (earlier l_H) are given higher priorities.

Highest Rate (HR), presented in [21], aims at minimizing the average latency of the queries running in the system. The priority value of each operator is equal to its *global output rate*, which represents the number of egress tuples that would be produced per time unit if that operator and all its downstream operators were executed. This policy prioritizes operators that are more productive (higher selectivity) and less costly (lower cost). Since the priorities depend on the features of multiple operators, we expect this policy's overhead to be higher than that of FCFS.

Chain policy [5] tries to minimize runtime memory usage. It groups operators based on how many tuples they discard and how quickly they do so and prioritizes operators that belong to the

Policy	Features	# Dims	Optimizes	Sections
FCFS	l_H	1	Max Latency	§ 7.3, § 7.4
HR	c, s	1	Mean Latency	§ 7.3, § 7.4
Chain	c, s, l_H	2	Memory	§ 7.3
Multi-Class	c, s, l_H	2	Custom	§ 7.4

Table 4: Scheduling policies studied in the evaluation.

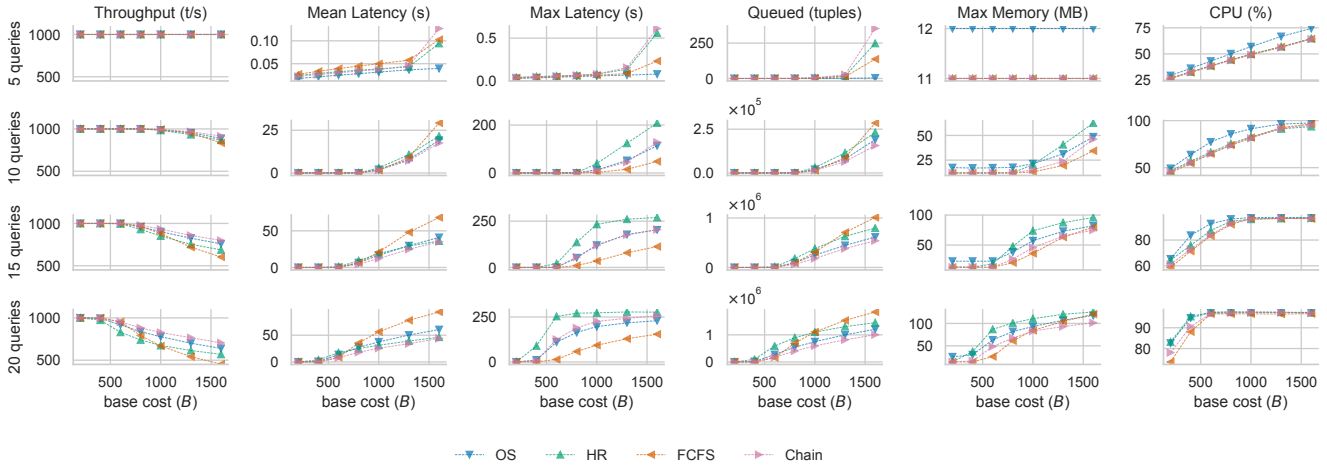


Figure 4: Comparison of the performance of four single-class scheduling policies.

groups that discard the most tuples for the least cost. If two operators have equal value of priority returned by the chain algorithm, the operator with the earliest head clock time is executed. Thus, the used intra-thread scheduling function g has two dimensions: the priority of the chain algorithm and the head clock time.

Multi-Class is a combination of multiple of the previous policies, which are applied depending on the priority class of each query. It is described in detail and studied in § 7.4.

7.3 Single-Class Scheduling

In this first part of the evaluation, we study the behavior of intra-thread scheduling functions g that assume that all the queries belong to the same priority class and only prioritize operators based on the value calculated by each specific policy.

Performance Comparison. Figure 4 compares the performance of scheduling using dedicated threads or custom scheduling with the FCFS, HR and Chain policies. We evaluate the mean throughput at the Ingress operators, the mean and maximum latency at the Egress operators and the total number of queued tuples. We also evaluate the maximum memory consumption and the average CPU utilization of the SPE process, including the scheduling overheads. The comparison is made for 5, 10, 15 and 20 queries running in parallel. When the processing load is much lower than the maximum capacity of the system (5 queries), OS scheduling can be optimal in throughput and latency, since there is no contention for resources. In such cases, the OS scheduler can respond faster than Haren's PTs which use an exponential back-off to conserve resources (Algorithm 1). However, OS scheduling's advantage diminishes as utilization and resource contention increase (>5 queries). For throughput, the Chain policy always performs better, which is expected since it prioritizes operators closer to the Ingress operators. Moreover, HR and FCFS policies optimize for mean and maximum latency respectively, as expected, outperforming OS scheduling. The Chain policy meets its goal of minimizing the total number of tuples in operator queues. Although FCFS results in more queued tuples, its memory consumption is usually lower or equal to Chain. We believe this is because different scheduling strategies result in different behaviors of the garbage collector. The CPU utilization is almost always lower for Haren than for OS scheduling.

Scheduling Overhead. Figure 5 shows a breakdown of the overheads introduced by the scheduling task T_S. More specifically, it shows the percentage of time spent (i) calculating priorities using the intra-thread scheduling function g (*Priority*), (ii) sorting the operators based on their priorities (*Sort*), (iii) updating the independent features and marking operators that need dependent feature updates (*Update*), (iv) running `coordinate` (Algorithm 3) (*Coord*)

Figure 5: Complete overheads of scheduling task T_S.

Figure 6: Overheads of the sequential part of T_S.

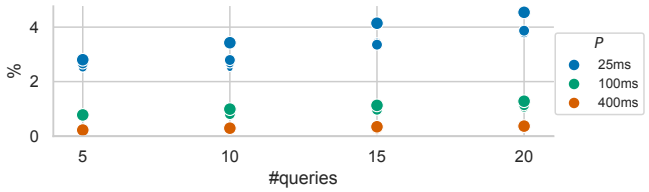


Figure 7: Algorithm 3 overhead for different P.

and (v) the total time spent in T_S (*Total*). As shown, the total scheduling overhead remains very low, almost always less than 2%. The overhead of computing operator priorities is negligible for FCFS since its intra-thread scheduling function g is simply the inverse value of one feature of a single operator. That overhead is higher for HR and Chain since they compute costly functions g involving the features of many operators. The time to sort operators by priority and update the independent features is negligible (lower than 1%).

The highest overhead of scheduling in most experiments is the duration of Algorithm 3 (Coord). In that phase, t^* runs the sequential part of T_S (Algorithm 3, L3-8), while all other PTs block. Figure 6 shows a breakdown of the sequential part, illustrating (i) the percentage of time spent updating the dependent features (*Update*), (ii) computing the inter-thread scheduling function f (*Assign*), and (iii) the total percentage of time spent in that part (*Total*). The figure shows that overheads usually increase with the number of queries. The HR policy has only an assignment overhead since it does not use any dependent features. On the other hand, FCFS and Chain also have an update overhead because they use the clock time, a dependent feature which needs updating. In all cases, the total time spent by t^* in the sequential part is less than the total duration of Algorithm 3 (Coord in Figure 5). The time difference is due to the synchronization overhead of the `entryBarrier` and `exitBarrier`. This overhead is needed not only to coordinate the PTs entering the different scheduling phases together but also to ensure memory visibility of actions happening before and after the barriers.

Figure 7 shows the duration of Algorithm 3 for different #queries and values of the scheduling period P. It depicts executions of the same policy (FCFS); the size of the dots indicates the magnitude of B (100-1600). In all cases, the overhead remains lower than 5%. Also, we observe an inverse relationship between the length of P and the overhead, which is expected since shorter P causes more frequent invocations of T_S. Additionally, the overhead increases with the #queries (and consequently, operators), since there is more data to update and synchronize. These results show a trade-off between the freshness of priorities and the overhead imposed by scheduling. Depending on the scheduling policy, it might be beneficial to pay a higher overhead for more up-to-date priorities, because the gain in performance will counterbalance the loss due to the overhead.

7.4 Multi-Class Scheduling

In this section, we focus on a more complex scheduling scenario and (i) study scheduling queries that belong to different priority classes, giving higher priority to the queries of higher classes and (ii) apply different scheduling policies for the queries belonging to each priority class. Scheduling based on priority classes can be important in many use cases of stream processing. For example, in edge and fog cyber-physical systems, there are frequently many streaming queries with different levels of *criticality* deployed to a single processing node [18, 19]. A smart vehicle, for instance, can be running many different streaming queries. Some of the queries can be very urgent, such as a query that detects obstacles, while others can be less urgent, such as a query that checks if the fuel is running low. Motivated by the use-case above, we construct the following evaluation scenario: each query belongs to a user-defined priority class which is provided to `Haren`, and represents the criticality of the query. Several synthetic queries are deployed using `Haren` having one of two possible priority class values, HIGH or LOW.

In our Multi-Class scheduling policy, queries of HIGH priority are always scheduled before LOW priority ones *(objective 1)*. HIGH priority queries are scheduled using the FCFS policy that minimizes the maximum latency *(objective 2)* while LOW priority queries are scheduled with the HR policy, to minimize the average latency *(objective 3)*. We run 3 HIGH and 10 LOW queries with different loads, comparing the behavior and ability of OS scheduling and `Haren` to meet the scheduling objectives. The base cost B is 600.

Scenario 1 (steady state). In this experiment, there are adequate processing resources, and the SPE is at a *steady state*. The HIGH

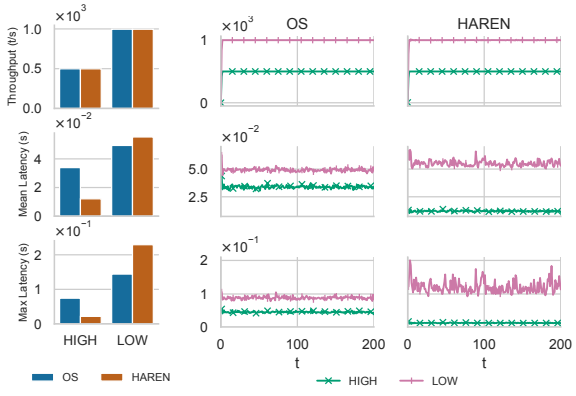


Figure 8: Multi-Class Scenario 1 (steady state)

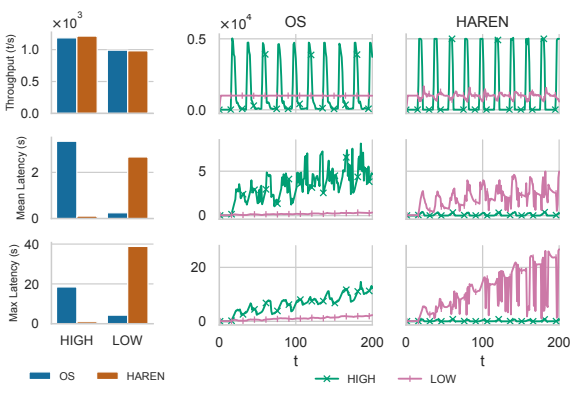


Figure 9: Multi-Class Scenario 2 (dynamic – high load)

and LOW data sources emit at a constant rate of 500 t/s and 1000 t/s respectively. Figure 8 shows the throughput, mean and max latency for the two query classes. Both scheduling techniques match the throughput of the data sources. However, Haren achieves a much lower max and mean latency for the HIGH queries (objective 2), while keeping the mean latency of the LOW queries at similar levels as the OS (objective 3). The overall performance of HIGH queries is higher than that of the LOW queries (objective 1). Since the policy does not optimize for the maximum latency of LOW queries, this metric shows a higher increase.

Scenario 2 (dynamic — high load). In this scenario, the source rate fluctuates and the system is in an overloaded state. The data sources of HIGH queries emit tuples at a rate of 5000 t/s for 5 seconds and then stop emitting for another 15 seconds. The data sources of the LOW queries emit at a constant rate of 1000 t/s, as before. Figure 9 shows the same performance metrics of the HIGH and LOW queries. Similarly to scenario 1, Haren prioritizes HIGH queries compared to the LOW ones, in contrast with OS scheduling (objective 1). More specifically, Haren achieves better throughput than OS for the HIGH queries, while it is slightly worse for the LOW ones. The figure shows that, for OS scheduling, the maximum latency of all queries keeps increasing. On the other hand, Haren dramatically reduces the maximum latency of HIGH queries (-17.4s) and at the same time keeps it at a near-constant level during the whole execution (0.1s), achieving objective 2. Moreover, the mean latency of the LOW priority queries increases but remains stable and at lower values (2.6s) than those achieved for HIGH queries by OS scheduling (3.5s), thus achieving objective 3. The max latency of LOW queries increases faster, which is expected since Haren's custom policy does not have this scheduling objective. The results highlight that, especially in the presence of resource contention, Haren's application-level scheduling allows the users to choose which metric (of which queries) they want to prioritize, until the load decreases or more resources become available.

8 RELATED WORK

Scheduling in data streaming can refer to resource scheduling (how to deploy operators, from one or more queries, to SPE instances within and across computational nodes [3, 13, 27–29]) and thread scheduling (how to allocate threads to operators within each SPE instance). These complementary views can be joint to meet performance metrics (e.g., latency) from both a top-down (e.g., to decide which node should run a certain query or operator) and a bottom-up perspective (e.g., to customize CPU threads allocation to operators). Since we focus on thread scheduling, Haren's approach is orthogonal to resource scheduling (see § 1) and can work in synergy with it. For a given resource allocation, Haren can take care of thread scheduling at each SPE instance (e.g., Flink TaskManager or Storm Worker [7, 24]) and run operators (that would otherwise be run by dedicated task/executor threads) based on the scheduling policies. The features can be retrieved either from the SPE's API or from secondary monitoring components (e.g., Flink's metric system).

Haren is mainly orthogonal to existing work, since it does not rely on any hard-coded policy but rather distills the functionality required from a scheduler to implement general, user-defined scheduling policies. We believe ours is the first work proposing and evaluating a concrete implementation of such a scheduler.

Many scheduling policies and metrics proposed in the literature aim at meeting the growing requirements that users have for streaming applications. The *First-Come-First-Serve (FCFS)* policy was first proposed in [6] to optimize for the maximum latency of streams of continuous requests, in the context of database and web servers, and has been further studied in the context of stream processing [22, 23]. The *Rate-Based (RB)* policy optimizes for the average latency of a single streaming query and was described in [25]. In [21], Sharaf et al. present an extension of the Rate-Based policy called *Highest Rate (HR)* that extends the former to multiple queries. Chandramouli et al. [10] introduce a metric called Mace (Maximum cumulative excess) and describe a scheduling framework for the StreamInsight SPE that uses this metric to accurately estimate the latency imposed by the stream processing pipeline. The *Chain scheduling* policy, described in [5], tries to minimize the runtime memory usage of multiple queries at the same time. It is proven to be near-optimal for many types of single-stream queries and also acceptable for multi-stream queries; it is also extended in [4] to take maximum latency into account. Aurora, a pioneer SPE, provided a detailed description of its scheduling policy [8, 9] based on two schedulers with different functionalities and goals. The first two-level scheduler schedules queries (superboxes) using *Round-Robin*, whereas operators (boxes) are scheduled with one of three policies that either optimize for average throughput (*Min-Cost*), average latency (*Min-Latency*, which is very similar to the Rate-Based policy) or available memory (*Min-Memory*). The second scheduler of Aurora aims at optimizing the *QoS* of the system by utilizing user-provided graphs that correlate the latency with the QoS of queries. The work explores various optimizations to minimize the scheduling overhead while matching user-defined goals.

When many heterogeneous queries run in the same node, it can be crucial to achieve *fairness*, i.e., balance the degree of slowdown experienced by co-scheduled queries. One way to express this notion is the *slowdown* or *stretch* [1, 16] metric. The *Longest Stretch First (LSF)* metric has been shown to optimize the maximum slowdown [1]. Sharaf et al. propose operator scheduling policies to optimize for latency or slowdown or to balance both of these metrics, either in the average or in the worst case [22, 23]. Heterogeneous queries deployed in the same system can exhibit different QoS requirements. Scheduling queries based on different priority classes is explored in [15], with the *Continuous Query Class* (CQC) scheduler, a two-level scheduler relying on *Weighted Round Robin* and *Highest Rate* schedulers [23]. CQC aims to minimize the latency of high-priority queries and maintain reasonable latency values for the low-priority ones. Pham et al. extend this work and explore the relationship between scheduling and load management in [19, 20]. Their scheduler and load manager work in synergy, exchanging runtime information to consistently honor the user-defined priorities of the queries while increasing the system's utilization.

9 CONCLUSIONS AND FUTURE WORK

We study the problem of thread scheduling in stream processing, searching for a solution that is not bound to a specific SPE implementation nor scheduling policy. As a result, we propose Haren, an

all-purpose scheduling framework that can be integrated into an SPE through a well-defined API and that allows users to define ad-hoc scheduling policies with minimal programming effort. Haren implements such policies efficiently by parallelizing the work to multiple processing threads in a transparent fashion. We thoroughly evaluate Haren and observe that its expressiveness and efficiency not only allow to define many of the scheduling policies in the literature but also outperform widely-adopted approaches in which SPEs rely on the Operating System scheduler.

Interesting future work studies include the possibilities given by the inter-thread deployment function of Haren to elastically adjust threads of an SPE and boost Haren's adaptivity by means of autonomous adjustments of its configuration parameters (e.g., the scheduling period P). Other interesting directions include a more in-depth exploration of Haren's behavior for complex queries that involve parallel branches [26] as well as for runtime changes of the queries or the policies used to schedule their operators.

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