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Optimizing the Energy Consumption of Continuous Query Processing with Mobile Clients

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Abstract—Complex event detection over data streams has become ubiquitous through the widespread use of sensors, wireless connectivity and the wide variety of end-user mobile devices. Typically, such event detection is carried out by a data stream management system executing continuous queries (CQs), previously submitted by the users. In this paper, we consider the situation where the results of the CQs, which are in the form of individual data streams, are disseminated to the users’ handheld, battery-operated devices over a shared broadcast medium. In order to reduce the overall energy consumption of the mobile devices, we propose BOSe*, a power-aware query operator placement algorithm that determines which part of a CQ plan should be executed at the data stream management system and which part should be executed at the mobile device. BOSe*’s effectiveness in reducing energy consumption, as well as response time under specific conditions, is evaluated using simulation, driven by parameters measured on real mobile devices.

I. INTRODUCTION

Research in energy conservation in mobile and wireless networks has always been driven by the fact that there is a gap between the energy consumed processing data compared to the energy consumed for transmitting or receiving data at a mobile device, in the favor of local processing. This is especially true as the CPUs of the mobile devices become even faster, with newer devices even featuring two-cores. This fact has led to the design principle of trading off communication energy consumption for computation energy consumption (e.g., [14]). In this paper, we apply this principle to minimize the energy consumption on mobile users’ hand-held, battery-operated devices of Data Stream Management Systems (DSMSs).

Specifically, we consider monitoring applications where mobile users register continuous queries (CQ) specifying events of interest to them to be efficiently executed by a DSMS over unbounded data streams. The results of CQs are also in the form of continuous data streams that are continuously disseminated to the mobile end-users over a shared broadcast wireless medium. As an example of a CQ submitted by a mobile user, consider the query of a trader which monitors stock price updates, at the floor of a market exchange (Fig. 1): it selects the stocks that are in the NASDAQ index (operator $O_1$); projects out the columns of no interest (operator $O_2$); joins the tuples with user’s portfolio to append the buying price (operator $O_3$); and finally, calculates the user’s profit in the last 5 minutes, every 30 seconds (operator $O_4$).

Our approach is to split the load of query processing between the DSMS and the mobile user devices themselves by opportunistically taking advantage of the reduced size of intermediate results to shorten the mobile devices’ listening time of the broadcast and, consequently, reduce their communication energy cost, at the cost of additional local processing. In our trader query example, the first two operators $O_1$ (select) and $O_2$ (project) are data reducing, while the operator $O_3$ (join) and $O_4$ (aggregation) could potentially be data expanding. Thus, $O_3$ and $O_4$ could be shipped to the mobile client, and the much smaller intermediate result produced by $O_2$ will be broadcast. Further, CQs often share prefixes which include the same operators (as in Fig. 1(b)), making it even more beneficial to broadcast intermediate results shared by multiple queries since the overall broadcast size will be reduced.

In our prior work in [12], we have laid the groundwork for our approach by proposing three operator placement algorithms assuming a simplistic CQ execution model. Of these, the BOSe (Broadcast-aware Operator Selection) algorithm was the best performing. Encouraged by our preliminary results, in this paper we present and evaluate BOSe* which is based on a realistic CQ execution model that supports operator sharing among queries and sharing of queries among users. Our results have also suggested that BOSe* reduces response times under specific conditions.

Contributions: This paper’s contributions can be summarized as follows:

1) We propose BOSe*, an operator placement algorithm, which takes into account the broadcast organization, sharing of operators and sharing of queries to provide the most overall energy savings at the mobile devices.
2) We present a heuristic parameterized variant of BOSe*, namely, BOSe-vlook, which significantly reduces the cost for generating high-quality operator placement plans which are comparable to those of the basic BOSe*.
3) We provide an extensive experimental evaluation, using parameters obtained from experiments using real mobile devices. Our results show that BOSe* can achieve an overall energy reduction of up to 53%.

Outline: Section II provides the system model. Section III presents BOSe* and Section IV describes its evaluation. Section V surveys related work. Section VI lists our findings.
II. SYSTEM MODEL

In our model, the DSMS implements as a core module a wireless disseminator which broadcasts the results of CQs to the mobile users (clients).

A. Data Stream Processing

A CQ evaluation plan generated by the query optimizer can be conceptualized as a data flow tree [1], [6], where the nodes are operators that process tuples and the edges represent the flow of tuples from one operator, e.g., $O_x$, to another, $O_y$ (Fig. 1(a)), where \( \text{upstream}(O_y) = O_x \) and \( \text{downstream}(O_x) = O_y \). Each operator is associated with a queue where input tuples are buffered until they are processed.

A single-stream query $Q_k$ has a single source operator, e.g., $O^k_1$ and a single output operator, e.g., $O^k_i$. Further, in a query plan $Q_k$, an operator segment $G^k_{x,y}$ is the sequence of operators that starts at $O^k_x$ and ends at $O^k_y$. If the last operator on $G^k_{x,y}$ is the output operator, then we simply denote that operator segment as $G^k_x$.

When two or more continuous queries share a common sub-expression, that sharing translates into identical prefix operator segments across the plans for those queries. In such case, the DSMS continuous query optimizer typically chooses to instantiate this prefix only once. The results produced by this prefix segment are shared among the remaining suffixes of the queries that share this prefix. For each operator $O_x$ in the shared segment, we define $Q(O_x)$ as the set of queries sharing $O_x$. For example, in Fig. 1(b), $Q(O_1) = Q(O_2) = \{Q_k, Q_j\}$. Another popular form of sharing which can be seen as a special case of operator sharing is when the same query is shared by more than one query then those results are also shared among the remaining suffixes of the queries that share this prefix.

In a query $Q_k$, an operator $O^k_x$ (or simply $O_x$) could be select ($\sigma$), project ($\pi$), aggregate (e.g., \( \sum \)), or join-table ($\bowtie_T$). Each operator is associated with three parameters:

- \( c_x \): the number of cycles needed to process an input tuple.
- \( s_x \): the ratio of output tuples produced by $O_x$ after processing one input tuple. Thus, $s_x$ is less than or equal to 1 for a filter operator and it could be greater than 1 for a join operator.
- \( p_x \): the ratio between the size of a tuple produced by $O_x$ (i.e., output size) to its size before being processed (i.e., input size). Thus, $p_x$ is less than or equal to 1 for a project operator and it may be greater than 1 for a join operator.

For an operator $O_x$, with \( \text{upstream}(O_x) = O_{x-1} \), we define the following characterizing parameters:

- \( t_{nx} \): is the number of tuples produced at the output of $O_x$ after processing the $t_{nx-1}$ tuples in its input queue: \( t_{nx} = t_{nx-1} \times s_x \).
- \( t_{sx} \): is the size of each tuple produced at the output of $O_x$ after processing a tuple in its input queue: \( t_{sx} = t_{sx-1} \times p_x \).
- \( d_{sx} \): is the size of the data block produced at the output queue of $O_x$ after processing a block of data from its input queue: \( d_{sx} = t_{sx} \times c_x \).

Notice that if $O_x$ is the output operator in query $Q_k$, then $d_{sx}$ is the total size of the data block produced by $Q_k$.

B. Wireless Broadcast

In this work, we adopt broadcast push ([3]) since it naturally complies with the DSMS access model where a client installs a CQ once and the server repeatedly broadcasts the new results as they become available. Hence, any number of clients can monitor the broadcast channel and retrieve data as it arrives, at a constant bandwidth speed: BW.

In our model, the wireless disseminator initiates a new broadcast cycle as soon as the previous one ends. Each cycle consists of a sequence of results which could be either a final result (i.e., produced at a query’s output operator) or an intermediate result (i.e., produced at a query’s internal operator). In general, we denote the broadcast result produced by $O_x$ as $D_x$ and its size in bytes as $|D_x|$. Moreover, if $O_x$ is shared by more than one query then those results are also shared on the broadcast and only appear once.

The result $D_x$ of an operator $O_x$ appears on the broadcast channel as a contiguous sequence of data packets preceded by a descriptor packet that contains an identifier of $Q(O_x)$ and the time offset to the next broadcast cycle. Accordingly, each client should tune to each broadcast cycle for results corresponding to its registered CQs. During tuning, the client’s network interface card (NIC) is in active mode consuming relatively large amounts of energy compared to when the client’s NIC is switched to an idle mode. Hence, the amount of energy consumed by a wireless client depends on the data organization [11], [10].

In this paper, we adopt two basic data organization schemes. The first data organization scheme uses sorted broadcast, where the broadcast server sorts the results according to the data size and the popularity of each result. In particular, each result $D_x$ is assigned a priority $P_x$ equal to $\frac{|D_x|}{|D_{max}|}$, where $R_x$ is the number of queries that share the result $D_x$ produced by operator $O_x$. That is, \( R_x = \left| \bigcup_{Q_i \in Q(O_x)} C(Q_i) \right| \). The broadcast is then organized in descending order of priority. This maintains a broadcast that follows the weighted shortest job first scheduling policy which has been shown to minimize total response time in shared resources [7].

Accordingly, a client $N_i$ that registered a set of queries $Q(N_i) = \{Q_1, Q_2, ..., Q_m\}$ will need to download a set of results (either final or intermediate) where each of those results might correspond to one or more queries in $Q(N_i)$. In
particular, $N_i$ will download results $\{D_1, D_2, ..., D_n\}$ where $n$ is the number of results and $n \leq m$. Hence, if the queries in $Q(N_i)$ do not share any operators then $n = m$, otherwise $n < m$. Finally, $N_i$'s tuning time $T_T(N_i)$ is computed as:

$$T_T(N_i) = \frac{|D_{\min}| + \sum_{i=1}^{n} |D_i|}{BW}, \forall y : P_j > P_{\min} \quad (1)$$

where $D_{\min}$ is the result with the minimum priority among all the results $\{D_1, D_2, ..., D_n\}$. In particular, the client will tune from the beginning of the broadcast downloading results for queries in its registered set and it will stay tuned until it downloads the last one (with $D_{\min}$) in that set.

The second data organization scheme uses an indexed broadcast, where the broadcast server attains an index at the beginning of each broadcast cycle (e.g., a (1,1) index [11]). The index contains an entry for each result $D_x$ on the broadcast in the form $<Q(D_x), t_s>$, where $t_s$ is the time offset of $D_x$ within the broadcast cycle. In this scheme, a client $N_i$ needs to first tune to the index packet to learn the broadcast times for each of the results corresponding to the queries that it has registered for, then power off its NIC until the time of the smallest of those timestamps, say $t_s$. At time $t_s$, $N_i$ powers on its NIC again, tunes into the broadcast to retrieve that result (i.e., $D_x$) and after it finishes fetching all of $D_x$'s data packets, powers off the NIC again until the next broadcast cycle or the second broadcast cycle, if there are no other timestamps remaining. The tuning time for a node $N_i$ in the indexed broadcast is computed as:

$$T_T(N_i) = \frac{\sum_{i=1}^{n} |D_i| + |Index|}{BW} \quad (2)$$

where $n$ is the number of results corresponding to $N_i$'s queries as defined before, $|D_x|$ is the size of each of those results, and $|Index|$ is the size of the index.

C. Mobile Clients

Mobile clients, serviced by the system, can register multiple queries and then listen to a broadcast medium to get their results. We assume that each mobile client is associated with a profile that includes the following four characteristics:

- $Speed(N_i)$: processing speed of the client in cycles per unit of time.
- $P_p(N_i)$: power consumed per unit of time of processing.
- $P_T(N_i)$: power consumed per unit of time of tuning (i.e., when the NIC is active).
- $E_{\text{PowerUp}}$: energy needed to power up the NIC.

Based on the client profiles, the energy consumption, and computational cost can be computed. Specifically the tuning energy, $E_{\text{Tune}}$ for a client $N_i$:

$$E_{\text{Tune}}(N_i) = T_T(N_i) \times P_T(N_i) + U(N_i) \times E_{\text{PowerUp}} \quad (3)$$

where $T_T(N_i)$ is the tuning time and $U(N_i)$ is the number of times the client needs to power up the NIC.

The processing power, $E_{\text{Process}}$ for a client $N_i$, given the processing time, $T_P$ as:

$$E_{\text{Process}}(N_i) = T_P \times P_p(N_i) \quad (4)$$

III. BOSe*: Broadcast Aware Operator Selection

In this section, we formalize the placement of CQ operators in DSMS environments with mobile clients and propose our new operator placement algorithms, BOSe* and its variant.

A. Problem Statement

Our goal is to design operator placement algorithms that work in synergy with the broadcast organization so that we minimize the total energy consumption at the mobile clients. The total energy consumption is the sum of two components: tuning and processing, which can be expressed as:

$$E_{\text{Total}} = E_{\text{Tune}} + E_{\text{Process}} \quad (5)$$

Given the clients’ profiles and their corresponding registered queries, an operator placement algorithm decides to shift some of the computation to the client if it is beneficial in reducing the overall total energy consumption. Specifically, for each query it splits its query plan into two segments, where the first segment is processed on the DSMS, whereas the second one on the clients who registered to the query. For instance, if client $N_i$ registered queries $\bar{Q}(N_i) = \{Q_j, Q_k\}$ and their plans were split at operators $O_2$ and $O_y$ respectively, then the operators in $G = G_{y+1, output}^k$ have to be processed on the client. The set of operators executed at $N_i$ is expressed as: $G = G_{y+1, output}^j \cup G_{y+1, output}^k$ to cover the case where the two segments share common operators and need to be instantiated only once on each client.

Thus, for a client $N_i$ running segments $G = G_{y+1, output}^j \cup G_{y+1, output}^k$, the processing time is computed as:

$$T_P(N_i) = \sum_{O_k \in G} \frac{c_k \times \text{tn}_k - 1}{Speed(N_i)} \quad (6)$$

Using Eq. 4 we can now find the processing energy $E_{\text{Process}}$ consumed by each wireless client $N_i$ for use in calculating the total processing power on each client in Eq. 5.

In our prior work [12], we proposed the following two algorithms along with BOSe (the preliminary version of BOSe*).

a) DataMinCut: minimizes the tuning energy expended by the clients. It does so by using the Max-flow Min-cut theorem, on the whole query network, which is cast into a flow-graph, to select the edges $E$ whose data will populate the broadcast. Each edge in the flow graph is labeled with the average data size flowing through it.

b) PowerMinCut: attempts to minimize the overall energy by choosing the edges that result in smallest total energy (tuning and processing) for the client. It augments the edge labels with the client processing energy cost of all the operators downstream of each edge. This algorithm neglects the broadcast organization and thus may result in suboptimal energy consumption as, depending on the broadcasting scheme, a local decision may negatively affect other clients.

B. Broadcast-aware Operator Selection (BOSe*)

BOSe* could be perceived as a hybrid of DataMinCut and PowerMinCut as it integrates the desirable features of each. On one hand, like DataMinCut, BOSe* tries to minimize the
length of the broadcast cycle to minimize tuning energy. On the other hand, BOSe*, like PowerMinCut, considers the extra energy needed for operator processing at the client.

BOSe* uses the DataMinCut output as a starting point and then applies a greedy selection process geared towards finding a segment of operators downstream from the current cut and reinstating them back on the server. Since DataMinCut gives the minimal broadcast size, that means that any reinstatement by BOSe* will incur an increase in the broadcast no matter what. However, BOSe* will only perform a reinstatement if its benefit in terms of reducing processing energy is greater than the cost incurred in terms of increasing tuning energy, which depends on the broadcast organization.

At each iteration, BOSe* examines all the current broadcast edges, \( E \). For each edge \( E_x \in E \), it generates a list of all the possible segments of operators following that edge, vertically as well as horizontally. That is, all the prefixes of the operator segments \( G_x^{j+1, output} \) for all of the queries \( Q_j \) in \( Q(O_x) \). It does this recursively by adding to the current segment, all possible combinations of operators connected to it (power-set), taken from the next level of operators. This process is performed for each edge in \( E \) and the segment with the highest impact in reducing total energy is selected and its operators are reinstated to the server. BOSe* repeats the selection process until no further improvement in energy is achievable.

**BOSe* optimization function:** Recall that at each step, BOSe* is expected to increase the tuning energy while decreasing the processing energy as compared to DataMinCut. Assume these changes are \( \Delta_{Tune} \) and \( \Delta_{Process} \), respectively. Hence, after BOSe makes a selection, the overall energy consumption from Eq. (5) can be expressed as:

\[
E_{Total} = (E_{Tune} + \Delta_{Tune}) + (E_{Process} - \Delta_{Process})
\]

Clearly, our objective is to select an operator segment which minimizes the value: \( \Delta_{Tune} - \Delta_{Process} \) which should also be less than zero. Thus, we simply need to compute that value for each operator segment consideration and select the one with the lowest value. To illustrate this process, assume that \( E_R \in E \). Further, assume that \( G \) is one of those prefixes under examination, which is considered a candidate to be moved from client \( N_i \) back to the server side. For instance, \( G \), in Fig. 2. Moving \( G \) back to the server will reduce the processing energy by the amount \( \Delta_{Process} \), computed as follows:

\[
\Delta_{Process} = \sum_{j \in G} \sum_{N_i \in C(Q_j)} \left( \frac{\text{Speed}(N_i)}{\text{Speed}(\text{E})} \times P_T(N_i) \right)
\]

Further, moving segment \( G \) back to the server entails replacing, in the broadcast \( E \), its input edge (i.e., edge \( E_R \)) with \( G \)'s output edges, say \( E_{A_1} \) and \( E_{A_2} \) (Fig. 3). The impact of this replacement operation, on the tuning energy (\( \Delta_{Tune} \)) depends broadcast organization.

In the case of sorted broadcast, removing \( E_R \) will reduce the tuning time for all clients \( N_i \) receiving data from \( E_R \). Additionally, it will also reduce the tuning time for all the clients waiting for results that appear after \( E_R \) on the broadcast cycle (\( N_R \)). This reduction per client is simply \( ds_R / BW \), where \( ds_R \) is the data size of associated with edge \( E_R \). Hence, the total reduction is computed as:

\[
\Delta_R = \frac{ds_R}{BW} \times \left( \sum_{N_i \in C(E_R)} P_T(N_i) + \sum_{N_i \notin C(E_R)} P_T(N) \right)
\]

Similarly, adding \( E_{A_1} \) will increase the tuning time for the clients \( N_i \) receiving data from \( E_{A_1} \) and will also increase the tuning time for all the clients waiting for results that appear after \( E_{A_1} \) on the broadcast cycle (Fig. 3), including any newly added edges which will appear after \( E_{A_1} \). This increase per client is simply \( ds_{A_1} / BW \), where \( ds_{A_1} \) is the data size associated with edge \( E_{A_1} \). This increase is computed as:

\[
\Delta_A = \sum_{A_i \in E_{A}} \frac{ds_{A_i}}{BW} \times \left( \sum_{N_i \in C(E_{A_i})} P_T(N_i) + \sum_{N_i \notin C(E_{A_i})} P_T(N) \right)
\]

where \( N_{A_i} \) is the set of clients waiting for results that appear after \( E_{A_i} \) on the broadcast cycle.

Moreover, under a sorted broadcast, the location of the new edge \( E_{A_1} \) on the broadcast cycle is determined according to each one’s data size. Since \( ds_{A_1} > ds_R, \forall i \), then \( E_{A_1} \) will appear at a further offset than \( E_R \)’s one. Therefore, when \( E_{A_1} \) replaces \( E_R \), the clients \( N_i \) which consume results in \( E_{A_1} \) will have to spend more tuning time to receive them than what they used to spend to receive \( E_R \). This translates into extra tuning energy which is computed as:

\[
\Delta_{R,A} = \sum_{A_i \in E_{A}} \sum_{E \in E_{E_{R,A}}} \frac{ds_E}{BW} \times P_T(N)
\]

where \( E_{E_{R,A}} \) is the set of edges on the broadcast cycle that appear after \( E_R \) and before \( E_{A_1} \).

Thus, \( \Delta_{Tune} \) for the sorted broadcast is computed as:

\[
\Delta_{Tune} = -\Delta_R + \Delta_A + \Delta_{R,A}
\]
In the case of indexed broadcast the optimization is simplified since the edge remove/add operation will only affect the client under examination without any impact on the other clients in the system (i.e., \( \Delta_{R,A} = 0 \) in Eq. 9). Thus, \( \Delta_{Tune} \) for the indexed broadcast is denoted by \( \Delta'_{Tune} = -\Delta'_{R} + \Delta'_{A} \), where equations 7 and 8 become:

\[
\Delta'_R = \sum_{N \in C(E_R)} \frac{ds_R}{BW} \times P_T(N) \\
\Delta'_A = \sum_{A_i \in S_A, N \in C(E_A)} \frac{ds_A}{BW} \times P_T(N)
\]

It is interesting to note that the above equations clearly reveal that BOSe* on indexed broadcast behaves like PowerMinCut on indexed broadcast. This fact is also confirmed by our experimental results.

Complexity and Approximation: The BOSe* algorithm is performing an exhaustive search over all possible combinations of operators both vertically and horizontally. The number of combinations for each edge in \( E \) is \( \sum_{x} (log_2 x^2) \). To reduce the search space we propose a parameterized version of BOSe, called BOSe-vlook\( (x) \), which limits the cardinality of the set taken from the power-set (as mentioned before) up to \( x \).

IV. EXPERIMENTAL EVALUATION

In this section, we illustrate the performance of our algorithms using our own simulator driven by parameters determined from experimental results using a mobile device.

A. Experimental Setup

The algorithms – DataMinCut, PowerMinCut, and BOSe* and its variant – are implemented in Java and run as they would on a real system. As a base case, we also implemented ServerOps which executes all the operators on the server and broadcasts the final results to the clients.

The workload used in the simulator is a complete plan of the registered CQs, along with the mobile clients’ profiles which include their speed and power consumption parameters for processing and tuning.

We measure the total energy consumption at all the mobile clients as the ratio of processing to tuning power of the nodes increases linearly from 0.01 to 0.65, while keeping the tuning power constant. The remaining parameters are summarized in Table I. It should be noted that from our measurements on real hardware we found these ratios to be between 0.0104 and 0.6572. The values reported are averages of 15 runs.

B. Experimental Results (Energy)

Sorted Broadcast: As Fig. 4 shows, BOSe* outperforms all other algorithms. ServerOps’ performance is constant because it runs all operators at the server side, and thus increasing the processing power of mobile clients will have no impact on its performance. It also shows that DataMinCut is linearly increasing because DataMinCut tries to minimize only the tuning energy and not the processing energy. Hence, DataMinCut selects the same set of edges for every setting regardless of the increase in power consumption needed for processing. PowerMinCut performs better than DataMinCut and ServerOps; however, it is oblivious to the broadcast organization as it considers each query individually without measuring the impact of its selected edge on the other clients in the system. BOSe* is always performing better than any of the other algorithms because it evaluates the different options taking into account both the broadcast organization and the processing power costs of operators running on the mobile clients, thus striking a fine balance between both tuning and processing energies. For instance, at a processing to tuning energy ratio of 0.01 BOSe* provides an improvement in energy of 50% over ServerOps and at 0.35 an improvement of 14%. In the extreme case of 0.65, it still provides a small improvement.

The heuristics BOSe-vlook\( (2) \) and BOSe-vlook\( (3) \) perform very similarly to BOSe*. The reduction in number of computations is very significant: 38% for BOSe-vlook\( (3) \) and 75% for BOSe-vlook\( (2) \), while the performance remains very close to the best (up to 99%) for BOSe-vlook\( (3) \).

Indexed Broadcast: Due to space limitations we omit these results; however they are similar to those seen in Fig. 4. For example the energy savings in this broadcasting scheme are 53% compared to ServerOps, at a ratio of 0.01. In this case BOSe* and PowerMinCut perform identically as the broadcast order does not effect the power consumption of the clients.
output data streams for scalability and energy savings.

In our work, we apply the same concept in disseminating a DSMS’s available bandwidth and allowing maximum scalability. In these schemes, data of interest for multiple clients is disseminated to the mobile users and which leads to an overall energy reduction up to 53% in energy in mobile devices. Our extensive experimental evaluation showed the effectiveness of BOSe* in distributing the query operators in a way that reduces the size of the query results that need to be continuously disseminated to the mobile users and which leads to an overall reduction up to 53% in energy in mobile devices, compared to the traditional centralized CQ processing at the DSMS.

### References