An Intelligent Scheme for Uncertainty Management of Data Synopses Management in Pervasive Computing Applications

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Abstract—Pervasive computing applications deal with the incorporation of intelligent components around end users to facilitate their activities. Such applications can be provided upon the vast infrastructures of Internet of Things (IoT) and Edge Computing (EC). IoT devices collect ambient data transferring them towards the EC and Cloud for further processing. EC nodes could become the hosts of distributed datasets where various processing activities take place. The future of EC involves numerous nodes interacting with the IoT devices and themselves in a cooperative manner to realize the desired processing. A critical issue for concluding this cooperative approach is the exchange of data synopses to have EC nodes informed about the data present in their peers. Such knowledge will be useful for decision making related to the execution of processing activities. In this paper, we propose an uncertainty driven model for the exchange of data synopses. We argue that EC nodes should delay the exchange of synopses especially when no significant differences with historical values are present. Our mechanism adopts a Fuzzy Logic (FL) system to decide when there is a significant difference with the previous reported synopses to decide the exchange of the new one. Our scheme is capable of alleviating the network from numerous messages retrieved even for low fluctuations in synopses. We analytically describe our model and evaluate it through a large set of experiments. Our experimental evaluation targets to detect the efficiency of alleviating the network from numerous messages retrieved while keeping immediately informed peer nodes for significant statistical changes in the distributed datasets.

Index Terms—Edge Computing, Edge Mesh, Internet of Things, Data Management, Data Synopsis

I. INTRODUCTION

The Internet of Things (IoT) provides a huge infrastructure where numerous devices can interact with end users and their environment to collect data and perform simple processing activities [29]. IoT devices can report their data to the Edge Computing (EC) infrastructure and Cloud for further processing. As we move upwards from the IoT to the EC and Cloud, we meet increased computational resources, however, accompanied by increased latency. EC has been proposed as the paradigm adopted to be close to the IoT platform and end users involving increased processing capabilities (compared to IoT) to reduce the latency we enjoy when relying to Cloud.

EC deals with the provision of storage and processing capabilities from various heterogeneous devices [29]. EC nodes can become the hosts of distributed datasets formulated by the reports of IoT devices. There, we can incorporate advanced services to produce knowledge and analytics to immediately respond to any request, thus, supporting real time applications.

The aforementioned distributed datasets become the subject of numerous requests having the form of processing tasks or queries. Various research efforts study the selection of data hosts based on their available memory and battery levels [1] to perform the execution of tasks/queries. The future of EC involves nodes that are capable of cooperating to perform the desired tasks/queries. Under this ‘cooperative’ perspective, having a view on the statistics of the available datasets may assist in the definition of efficient tasks/query allocations.

For instance, an EC node may decide to offload a task/query for various performance reasons. The research community has already proposed data migration [9] as a solution to efficiently respond to requests. However, migrating huge volumes of data may jeopardize the stability of the network due to the increased bandwidth required to perform such an action. A solution is the offloading of tasks/queries, however, the allocation decision should be based on the data present in every peer node. The decision making should be realized upon the statistics of the available datasets to conclude the most appropriate allocation.

In this paper, we focus on the autonomous nature of EC nodes and propose a scheme for distributing data synopses to peers. We argue for the dissemination of the synopsis of each dataset to have the insight on the data present in peers. We propose the monitoring of synopses updates and detect when a significant deviation (i.e., the magnitude) with the previous reported synopsis is present. We define an uncertainty driven model under the principles of Fuzzy Logic (FL) [30] to decide when an EC node should distribute the synopsis of its dataset. The uncertainty is related to the ‘threshold’ (upon the differences of the available data after getting reports from IoT devices) over which the node should disseminate the current synopsis.

We monitor the ‘statistical significance’ of synopses updates before we decide to distributed them in the network.
This way, we want to avoid the continuous distribution of synopses especially when no significant difference is present. We consider the trade off between the frequency of the distribution and the ‘magnitude’ of updates. We can accept the limited freshness of updates for gaining benefits in the performance of the network. Our FL-based decision making mechanisms adopts Type-2 FL sets to cover not only the uncertainty in the decision making but also in the definition of membership functions for every FL set. We apply our scheme upon past, historical observations (i.e., synopses updates) as well as upon future estimations. We adopt a forecasting methodology for estimating the ‘trend’ in synopses updates. Both, the view on the past and the view on the future are fed into our Type-2 FL System (T2FLS) to retrieve the Potential of Distribution (PoD). Two PoD values (upon historical values and future estimations) are smoothly aggregated through a geometrical mean function [27] to finally decide the dissemination action. Our contributions are summarized by the following list:

- We provide a monitoring mechanism for detecting the magnitude of the updated synopses;
- We deliver a forecasting scheme for estimating the future realizations of data synopses;
- We describe and analyze an uncertainty driven model for detecting the appropriate time to distribute data synopses to peer nodes;
- We report on the experimental evaluation of the proposed models through a large set of simulations.

The paper is organized as follows. Section II presents the related work while Section III formulates our problem and provides the main notations adopted in our model. In Section IV, we present the envisioned mechanism and explain its functionalities. In Section V, we deliver our experimental evaluation and conclude the paper in Section VI by presenting our future research directions.

II. RELATED WORK

A significant research subject in EC is resource management. It is critical to adopt efficient techniques to resources allocation either in the form of scheduling or in the form of the allocation of tasks/queries to the appropriate resources. The ultimate goal is to increase the performance and facilitate the desired processing and timely provide responses. Currently, EC nodes adopt the following models to execute tasks/queries [37]: (i) through an aggregation model where data coming from multiple devices can be collected and pre-processed in an edge node [38]. Data are locally processed before they are transferred to the Cloud limiting the time for the provision of the final response; (ii) through a ‘cooperative’ model where EC nodes can interact with IoT devices having processing capabilities to offload a subset of tasks [39]. Devices and EC nodes should exhibit a low distance, otherwise, their interaction may be problematic; (iii) through a ‘centralized’ approach where edge nodes act as execution points for tasks/queries offloaded by IoT devices [31]. EC nodes exhibit higher computational capabilities than IoT devices and can undertake the responsibility of performing ‘intensive’ tasks, however, under the danger of being overloaded. Current research efforts related to tasks/queries management at EC nodes focus on caching [10], context-aware web browsing [32] and video pre-processing [35]. A number of efforts try to deal with the resource management problem [6], [13], [34], [37]. Their aim is to address the challenges on how we can offload various tasks/queries and data to EC nodes taking into consideration a set of constraints, e.g., time requirements, communication needs, nodes’ performance, the quality of the provided responses and so on and so forth.

The current form of the IoT and EC involves numerous devices that collect, report and process data. Due to the huge amount of data, data synopses can be useful into a variety of IoT/EC applications. Synopses depict the ‘high’ level description of data and represent their statistics [4]. The term ‘synopsis’ usually refers in (i) approximate query estimation [11]; we try to estimate the responses given the query. This should be performed in real time. The processing aims to estimate the data that will better ‘match’ to the incoming queries; (ii) approximate join estimation [5], [16]: we try to estimate the size of a join operation that is significant in ‘complex’ operations over the available data; (iii) aggregate calculation [12], [15], [17], [23]: the aim is to provide aggregate statistics over the available data; (iv) data mining mechanisms [2], [3], [33]: some services may demand for synopses instead of the individual data points, e.g., clustering, classification. In any case, the adoption of data synopses aims at the processing of only a subset of the actual data. Synopses act as ‘representatives’ of data and usually involve summarizations or the selection of a specific subset [22]. These limited representations reduce the need for increased bandwidth of the network and can be easily transferred in the minimum possible time. Some synopses definition techniques involve sampling [22], load shedding [7], [36], sketching [8], [28] and micro cluster based summarization [2]. Sampling is the easiest one targeting to the probabilistic selection of a subset of the actual data. Load shedding aims to drop some data when the system identifies a high load, thus, to avoid bottlenecks. Sketching involves the random projection of a subset of features that describe the data incorporating mechanisms for the vertical sampling of the stream. Micro clustering targets to the management of the multi-dimensional aspect of any data stream towards to the processing of the data evolution over time. Other statistical techniques are histograms and wavelets [4].

III. PRELIMINARIES AND PROBLEM DESCRIPTION

We consider a set of $N$ EC nodes $N = \{n_1, n_2, \ldots, n_N\}$, with their corresponding datasets $D = \{D_1, D_2, \ldots, D_N\}$. Every dataset $D_i = \{x_i\}_{j=1}^{m_i}$ contains $m_i$ real-valued contextual multidimensional data vectors $x = [x_1, x_2, \ldots, x_d] \in \mathbb{R}^d$ of $d$ dimensions. Every dimension refers to a contextual attribute (e.g., temperature, humidity). Contextual data vectors are reported by IoT devices that capture them through interaction with their environment. Contextual data vectors become the basis for knowledge extraction for every $n_i$. An arbitrary
methodology is adopted like a regression analysis, classification tasks, the estimation of multivariate and/or univariate histograms per attribute, non-linear statistical dependencies between input attributes and an application-defined output attribute, clustering of the contextual vectors, etc. Without loss of generality, we assume the online knowledge extraction model as the statistical synopsis $S$. $S$ is represented by $l$-dimensional vectors, i.e., $s = [s_1, s_2, \ldots, s_l]^T \in \mathbb{R}^l$. A statistical synopsis $S_i$ is the summarization of $D_i$ located at $n_i$. We obtain $N$ data synopses $S_1, \ldots, S_N$ represented via their synopsis vectors. Given synopses, EC nodes, initially, are responsible for maintaining their up-to-date synopses as the underlying data may change (e.g., concept drift). Additionally, EC nodes try to act in a cooperative manner and decide to exchange their synopses regularly. Through this approach, EC nodes can have a view on the statistical properties of datasets present in their peers. Based on that, we can gain advantage on preforming decision making for allocating tasks/queries and deliver analytics taking into consideration the data synopses distributed at the EC network.

Arguably, there is a trade off between the communication overhead and the ‘freshness’ of synopses delivered to peer nodes. EC nodes can share up-to-date synopses every time a change in the underlying data is realized at the expense of flooding the network with numerous messages. Recall, that EC nodes are connected with IoT devices that are continuously reporting data vectors in high rates. However, in this case, peer nodes enjoy fresh information increasing the performance of decision making. The other scenario is to postpone the delivery of synopses, i.e., to reduce the sharing rate expecting less network overhead in light of ‘obsolete’ synopses. In this paper, we go for the second scenario and try to detect the appropriate time to deliver a synopsis to peer nodes. The target is to optimally limit the messaging overhead. The idea is to let EC nodes to decide the ‘magnitude’ of the collected statistical synopsis before they decide a dissemination action. Obviously, there is uncertainty around the amount of magnitude that should be realized before we fire a dissemination action. We propose an uncertainty driven mechanism, i.e., out T2FLS that results the PoD upon past synopsis observations and its estimated values. In any case, EC nodes are forced to disseminate synopses at pre-defined intervals even if no delivery decision is the outcome from our model. We have to notice that, to avoid bottlenecks in the network, we consider the pre-defined intervals to differ among the group of EC nodes. This ‘simulates’ a load balancing approach avoiding to have too many EC nodes disseminating their synopses at the same time.

Our T2FLS is fed by the most recent $S$ as well as with its future realizations. Every EC node monitors significant changes in the local synopsis as more contextual data are received from IoT devices. Based on this local monitoring, implicitly, we incorporate into the network edge the necessary ‘randomness’ in the conclusion of the final decision, thus, potentially avoiding network flooding. The discussed ‘randomness’ is enhanced by different data arriving to the available nodes and their autonomous decision making. Such ‘randomness’ can assist in limiting the possibility of deciding the delivery of synopses at the same time, thus, we can limit the possibility of overloading the network. Let us consider that at the discrete time instance $t$ a new data vector arrives in $n_i$. Afterwards, the corresponding synopsis $s_i$ should be updated to conclude the new $s_i'$. Let $e_i$ be the difference over the current, last sent synopsis $s_i$ and the new, the updated one, $s_i'$. We call this error/difference as the update quantum, i.e., the magnitude of the difference between $s_i$ and $s_i'$. $n_i$ calculates $e_i$ at consecutive time steps. $e_i$, in a simplistic way, can be concluded by adopting the sum of differences between two consecutive synopsis for every dimension. Obviously, we can adopt any desired synopses realization technique as mentioned above. $e_i$ may be positive or negative, i.e., a new vector can increase or decrease the value of each dimension. For facilitating our calculations, we are based on the absolute value for any difference. EC nodes should delay the delivery of $s_i'$ until they see that a significant difference, i.e., a high magnitude of $e_i$ is present. In that time, it is necessary to have the peer nodes informed about the new status of the local dataset. We define the update epoch as the time between disseminating two consecutive synopsis updates. The update epoch is realized at pre-defined intervals, $T, 2T, 3T, \ldots$ ($T > 0$). To describe our solution, we focus on an individual interval, e.g., $[1, 2, \ldots, T]$. At each $t \in [1, 2, \ldots, T]$, EC nodes check the last $e_i$ realizations and feed them into our T2FLS to see if they excuse the initiation of the dissemination process. This action should be realize till $T$. If no dissemination decision is made till $T$, EC nodes start the dissemination no matter the observed magnitude. EC nodes also ‘reason’ over the time series of update quanta $\{e_i\}$ with $t = 1, 2, \ldots, T$. EC nodes ‘project’ the time series to the future through the adoption of a forecasting technique. Again, the projection of update quanta is fed into the T2FLS to generate the PoD upon the future estimations of $e$. The final goal is to accumulate as much as possible $e$ before we decide the dissemination action. When the accumulated magnitude is relatively high, EC nodes decide to ‘stop’ the monitoring process, disseminate the updated synopsis and ‘start off’ a new monitoring/update epoch.

IV. UNCERTAINTY DRIVEN PROACTIVE SYNOPSIS DISSEMINATION

The Proposed Fuzzy Reasoning Process. For describing the proposed T2FLS, we borrow the notion of our previous efforts (in other domains) presented in [20], [21]. T2FLS is adopted locally at every node at $t$ by fusing the past $e_i$ observations and future $e_i$ realizations. $e_i$ is adopted as the indication whether the current update quanta significantly deviate from their past and future short-term trends. The envisioned fusion of update quanta is achieved through a finite set of Fuzzy Inference Rules (FIRs). FIRs incorporate and ‘combine’ past quanta or future estimations (two different processes) to reflect the PoD. Actually, we ‘fire’ two consecutive times the T2FLS for the last three (3) quanta realizations, i.e.,
Our T2FLS, defines the fuzzy knowledge base for every \( n_i \), e.g., a set of FIRs like: ’when the past/future quanta exhibit a significant difference from the last synopsis delivery, the PoD for initiating the delivery of the new synopsis might be also high’. We rely on Type-2 FL sets as the ‘typical’ Type-1 sets and the FIRs defined upon them involve uncertainty due to partial knowledge in representing the output of the inference [26]. The limitation in a Type-1 FL system is on handling uncertainty in representing knowledge through FIRs [18], [26]. In such cases, uncertainty is observed not only in the environment, e.g., we classify the PoD as ‘high’, but also on the description of the term, e.g., ‘high’, itself. In a T2FLS, membership functions are themselves ‘fuzzy’, which leads to the definition of FIRs incorporating such uncertainty [26].

FIRs refer to a non-linear mapping between three inputs: (i) when focusing on the past quanta, we take into consideration the following as the inputs into the T2FLS: \( e_{t-2}, e_{t-1}, e_t \); (ii) when focusing on the future quanta, we take into consideration the following as the inputs into the T2FLS: \( e_{t+1}, e_{t+2}, e_{t+3} \). The outputs are \( \text{PoD}_p \) and \( \text{PoD}_f \), respectively. The antecedent part of FIRs is a (fuzzy) conjunction of inputs and the consequent part of the FIRs is the PoD indicating the belief that an event actually occurs. The proposed FIRs have the following structure: if \( e_{t-2} = A_{1k} \) and \( e_{t-1} = A_{2k} \) and \( e_t = A_{3k} \) THEN \( \text{PoD}_p = B_k \). If \( e_{t+1} = A_{1k} \) and \( e_{t+2} = A_{2k} \) and \( e_{t+3} = A_{3k} \) THEN \( \text{PoD}_f = B_k \),

where \( A_{1k}, A_{2k}, A_{3k} \) and \( B_k \) are membership functions for the \( k \)-th FIR mapping \( e_1, e_j, e_k \) and \( \text{PoD}_m \), \( i \in \{t-2, t+1\}, j \in \{t-1, t+2\}, k \in \{t, t+3\} \) and \( m \in \{p, f\} \). For FL sets, we characterize their values through the terms: low, medium, and high. The structure of FIRs in the proposed T2FLS involve linguistic terms, e.g., high, represented by two membership functions, i.e., the lower and the upper bounds [25]. For instance, the term ‘high’ whose membership for \( x \) is a number \( g(x) \), is represented by two membership functions defining the interval \( [g_L(x), g_U(x)] \). This interval corresponds to a lower and an upper membership function \( g_L \) and \( g_U \), respectively (e.g., the membership of \( x = 0.25 \) can be in the interval \([0.05, 0.2]\)). The interval areas \([g_L(x_j), g_U(x_j)]\) for each \( x_j \) reflect the uncertainty in defining the term, e.g., ‘high’, useful to determine the exact membership function for each term. Obviously, if \( g_L(x) = g_U(x) \), for every \( x \), we obtain a FIR in a Type-1 FL system. The interested reader could refer to [25] for information on reasoning under Type-2 FIRs.

**Time Series Forecasting.** Exponential smoothing [19] is a time series estimation methodology for univariate data. The method can be easily extended to detect the trend or seasonal components on data. We have to notice that as we adopt the specific methodology as it is fast, is easily adapted to frequent changes of data and performs better than other techniques (e.g., moving average), especially for a short-term time horizon. Exponential smoothing is similar to the weighted sum of past observations, however, it adopts a decay factor for decreasing weights based on the index of the past observation. In our model, we adopt the double exponential smoothing for estimating \( e_{t+1}, e_{t+2}, e_{t+3} \) based on all the available/calculated synopsis quanta. Recall that \( e_t \) exhibits the statistical difference (e.g., the sum) of the current and the previous disseminated synopsis. Hence, we can rely on the univariate scenario hiding all the statistics for each individual dimension. This is an ‘abstraction’ strategically adopted in our model. In the first place of our future research plans is the application of forecasting techniques for each individual dimension, then, aggregating them to derive the final estimated update quanta. Let all the available quanta be \( e_1, e_2, \ldots, e_t \). When applying the double exponential smoothing model, the following equations hold true: \( v_j = \alpha e_j + (1-\alpha)(v_{j-1} + b_{j-1}) \), \( b_j = \beta(v_j - v_{j-1}) + (1-\beta)b_{j-1} \), where \( v_1 = e_1 \) & \( b_1 = e_2 - e_1 \). Additionally, \( \alpha \in (0, 1) \) is the data smoothing factor and \( \gamma \in (0, 1) \) is the trend smoothing factor. The method adopts two smoothing factors to control the decay of data and the decay of the influence of the change in the trend of data. For performing a forecasting for additional data in the future, we adopt the following equation: \( v_{t+k} = v_t + b_t \). Based on the above, we can easily get \( e_{t+1}, e_{t+2}, e_{t+3} \) quanta fed into our T2FLS to retrieve the \( \text{PoD}_f \).
When $\phi \to 0$, our model manages to conclude immediately the dissemination action. Additionally, we define the metric $\delta$ i.e., $\delta = \frac{1}{T} \sum_{t} \{ |s' - s| \}$. $\delta$ represents the average magnitude of the difference between the current and the new synopses. Through the use of $\delta$, we want to present the ability of the proposed model to ‘react’ even in limited changes in the updated synopses (we target a $\delta \to 0$). The magnitude is calculated at $t^*$. The ability of the proposed system to avoid the overloading of the network and limiting the required number of messages is exposed by $\psi$. The following equation holds true: $\psi = \frac{|t^*|}{|t^*|_c \in [1, T]}$ $(\psi \in [0, T])$ where $|t^*|_c \in [1, T]$ represents the number of times that the model stops in the interval $[1, T]$. When $\psi \to 1$ means that the proposed model stops frequently, thus, multiple messages conveying the calculated synopses are transferred through the network. When $\psi \to T$ means that our model does not stop frequently, thus, the calculated synopses are delivered after the expiration of the window $T$. For our experimentation, we adopt the dataset presented in Intel Berkeley Research Lab [14]. It contains measurements from 54 sensors deployed in a lab. We get the available measurements and simulate the provision of context vectors to calculate the synopses and the update quanta (they are relized in the interval $[0, \infty]$) in a sequential order. We also pursue a comparative assessment for the UDDM with: (i) a baseline model (BM) that disseminates synopses when any change is observed over the incoming data; (ii) the Prediction based Model (PM) [24]: PM proceeds with the stopping decision only when the estimation of the future update quanta violates a threshold. We perform simulations for $E = 1,000$ and $T \in \{10, 100, 1,000\}$. In every experiment, we run the UDDM and get numerical results related to the mean values of the aforementioned metrics (we adopt $\theta \in \{0.60, 0.75\}$ for the UDDM and the PM).

**Performance Assessment.** In Fig. 1, we present our results for the $\phi$ metric. We observe that the adoption of a low $\theta$ (threshold for deciding the dissemination action) and a low $T$ (deadline to conclude the distribution of synopses) lead to an increased time for the final decision. Even in that case, the required time is around 30% of the total deadline $T$. When $\theta$ and $T$ are high, the percentage of $T$ devoted to conclude the dissemination decision is very low. Actually, the proposed system manages to deal with the final decision as soon as it detects that update quanta are aggregated over time even in small amounts. This can be realized in early monitoring rounds due to the dynamic nature of the incoming data. Recall that we adopt a time series that consists of sensory data retrieved by a high number of devices that are, generally, characterized by their dynamic nature.

In Table I, we present our results related to the $\delta$ metric, i.e., the update quanta at the time when the dissemination action is decided. We observe that the UDDM requires a higher magnitude than the BM and the PM before it concludes the dissemination action. This stands for both experimental scenarios, i.e., $\theta \in \{0.6, 0.75\}$. In general, there is an increment in $\delta$ as $T$ increases. Additionally, the PM exhibits the lowest $\delta$ outcome, i.e., the update quanta for which a dissemination action is decided. These results present the ‘attitude’ of the proposed model to wait and aggregate update quanta in order to alleviate the network from an increased number of messages.

**Table II**

**Experimental outcomes for the $\delta$ metric**

| T   | UDDM | BM | PM | UDDM | BM | PM |
|-----|------|----|----|------|----|----|
| 10  | 16.42| 13.87| 13.87| 15.82| 12.05| 8.61|
| 100 | 20.95| 17.76| 17.02| 17.60| 15.59| 13.92|
| 1,000 | 19.62| 17.68| 16.34| 20.55| 17.79| 16.63|

Table II depicts our experimental evaluation related to the $\psi$ metric. We observe that the UDDM demands for less dissemination messages compared with the BM & PM. As $T \to 1,000$, BM and PM exhibit an increased number messages. Approximately, they deliver the update quanta at every monitoring round. The proposed model decides the dissemination of messages every 2.5 (approximately) monitoring rounds for the experimental scenario where $\theta = 0.6$. When $\theta = 0.75$, we observe an increment in the dissemination activity, i.e., for every 1.5 monitoring rounds.

**VI. Conclusions**

One of the most significant research subjects at the Edge Computing (EC) is the management of data coming from devices active in the Internet of Things (IoT). The reason is that the IoT will become the core infrastructure for hosting future applications. This means that IoT should be supported by efficient services that build upon the collected data. Data management at the EC provides many benefits with the most important of them to be the minimization of the latency in the provision of responses in tasks/queries. A set of EC nodes can be adopted to become the hosts of the collected data and the processing entities being very close to end users and the IoT.
infrastructure. We argue on the cooperative approach that EC nodes should follow in order to conclude advanced processing mechanisms. Under this cooperative model, EC nodes could exchange the statistical synopses of their datasets to support the efficient decision making of their peers towards realizing the most productive tasks/queries allocations. This decision making mechanism is ‘fired’ when an EC node decides to offload the incoming tasks/queries. In this paper, we present a novel, uncertainty driven model to reason over the appropriate time to exchange data synopses. Our aim is to provide a scheme that minimizes the number of messages circulated in the network, however, without jeopardizing the freshness of the exchanged statistical information. We discuss our model adopting the principles of Fuzzy Logic (FL) and present the relevant formulations. EC nodes monitor their data and decide when it is the right time to deliver the current data synopsis. Our experimental evaluation shows that the proposed scheme can efficiently assist in the envisioned goals being evidenced by numerical results. In the first place of our future research plans, it is to incorporate a deep machine learning model in the uncertainty management scheme. Additionally, we want to involve more parameters in the decision making mechanism like a ‘snapshot’ of the current status of every EC node.

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