Satellite Earth Station (SES) Selection Method for Satellite-based Sensor Networks

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***Abstract*— The reference network is composed of a group of wireless sensors directly in view of a Cluster of Satellite Earth Stations (CoSES), which convey the information coming from the sensors to a destination Remote Monitoring Host (RMH). More than one Satellite Earth Station (SES), all in this letter, within the cluster receive the information packets but to avoid wasting bandwidth and energy only one of them stores the packets coming from a specific sensor and forwards them to the destination through the satellite channel. This letter proposes a method to select the transmitting SES so to minimize the distance with a situation considered ideal for a set of metrics: packet loss rate, average communication delay, and average energy consumption.**

***Index Terms*— Satellite sensor networks, multi attribute programming, network optimization, performance evaluation.**

I. Introduction

MONITORING systems are often based on Satellite-based Sensor Networks (SSNs) where Satellite Earth Stations (SESs) gather information (e.g., measures of physical quantities) from a wireless sensor network and use the satellite channel to send it to a Remote Monitoring Host (RMH). Satellite links are often affected by fading that can extend up to complete outage (SES failure). Similarly wireless links connecting sensors to SESs may be unreliable.

The use of multiple SES structures [1] may help mitigate the problem. On one hand, the use of a Cluster of SESs to which part of the sensors (all, in this letter) address information increases the probability that the information arrives at the destination, also in case of SES or wireless channel failure. On the other hand, if redundant information received by SESs were entirely transmitted through the satellite link, the cost in energy and overload would be unacceptable. The correct use of this type of network implies low probability to lose information, low average delay, and low energy consumption, which are the performance metrics considered in this letter.

II. SES Selection Algorithm

Fig. 1 shows the network used as reference in this letter. The Cluster of Satellite Earth Stations (CoSES) is composed of J stations. N sensors are connected to all SESs in the Cluster through wireless channels. SESs communicate with the destination RMH through satellite links. The aim is to choose the SES that forwards the information packets of a given sensor so to minimize the distance between the performance vector composed of normalized measured metrics and ideal values of the same normalized metrics, defined in the reminder of the paper. The choice is performed for each packet when it arrives at the SESs on the basis of a decision taken by virtual entities called Decision Makers (DMs), which are supposed located at the destination. Physical location may change without affecting the idea but only the implementation of the algorithm. The number of DMs is the same of the number of sensors N. $DM^{(n)}$ is the Decision Maker for the n-th sensor. It takes the decision about which SES must forward the packets of the sensor n at fixed instants $t_{D,h}^{(n)}$, $n \in [1, N]$, $h \in \mathbb{N}$. The decision is valid for the overall length of the h-th decision period for the sensor n $T_{D,h}^{(n)} = \left[t_{D,h+1}^{(n)} - t_{D,h}^{(n)}\right]$, $n \in [1, N]$, $h \in \mathbb{N}$, which is kept fixed $\forall h$, $\forall n$ in this letter. After the decision, DMs transmit the choice to the SESs that apply the forwarding/not forwarding strategy. Being the metrics possibly in contrast each other (i.e. increasing one may imply decreasing another), the selection algorithm is based on the *Multi Attribute Decision Making (MADM)* theory [2].

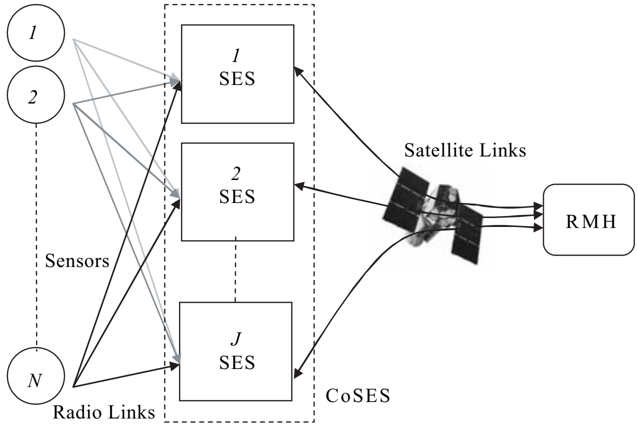

Fig. 1. Satellite-based sensor network.

Formally speaking: the index $k \in [1, K]$ identifies the metrics; $j \in [1, J]$ identifies each SES (i.e. the alternative that can be chosen) within the Cluster. There is one decision matrix for each $DM^{(n)}$. $\hat{X}_{jk}^{n}(t)$ is the value of the metric measured at the time t for the n-th sensor when the j-th SES is used. $X_{jk}^{n}(t) = \hat{X}_{jk}^{n}(t)/ \max_j \hat{X}_{jk}^{n}(t)$ is the normalized metric, also called attribute, over its maximum measured value. For $DM^{(n)}$, $n \in [1, N]$ the vector containing the attributes related to the j-th alternative, at the time t, is:

$$A_j^n(t) = \left[X_{j1}^n, ..., X_{jk}^n, ..., X_{jK}^n\right] \tag{1}$$

The matrix $J \times K$ the attributes for $DM^{(n)}$ at the time t for

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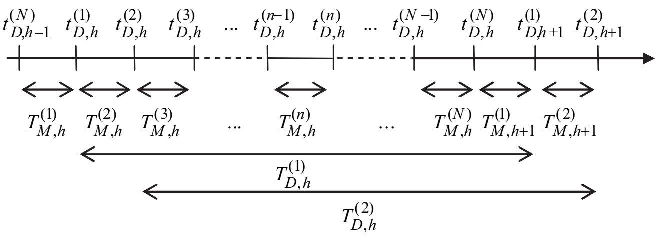

Fig. 2. Measure phases and decision instants.

all possible J choices is:

$$\mathbf{A}^n(t) = \begin{bmatrix} X_{11}^n & ... & X_{1k}^n & ... & X_{1K}^n \\ ... & ... & ... & ... & ... \\ X_{j1}^n & ... & X_{jk}^n & ... & X_{jK}^n \\ ... & ... & ... & ... & ... \\ X_{J1}^n & ... & X_{Jk}^n & ... & X_{JK}^n \end{bmatrix} \quad (2)$$

To make a numerical example: there are two possible SESs ($j = 1$ and $j = 2$) and two metrics, packet loss rate ($k = 1$) and average packet delay ($k = 2$) measured in [ms]. If the metrics at a given time instant t for the sensor n are: $\hat{X}_{11}^n(t) = 0.1$, $\hat{X}_{12}^n(t) = 16$ [ms] and $\hat{X}_{21}^n(t) = 0.2$, $\hat{X}_{22}^n(t) = 13$ [ms]. The attributes are: $X_{11}^n(t) = 0.1/0.2$, $X_{12}^n(t) = 16/16$, $X_{21}^n(t) = 0.2/0.2$, $X_{22}^n(t) = 13/16$. The attributes' vectors are: $A_1^n(t) = [0.5, 1]$ and $A_2^n(t) = [1, 0.813]$.

The selection algorithm is based on the knowledge of the ideal values, called *utopia point*, characterized by the ideal vector of attributes ${}^{id}A^n(t)$ at the time t, defined in (3).

$${}^{id}A^n(t) = \left[{}^{id}X_1^n, ..., {}^{id}X_k^n, ..., {}^{id}X_K^n\right] \quad (3)$$

Each component of the vector is:

$${}^{id}X_k^n = \left\{ X_{jk}^n : j = \arg\min_{j\in[1,J]} X_{jk}^n \right\}, \forall k \in [1, K] \quad (4)$$

In practice, ${}^{id}A^n(t)$ is an utopia vector selecting the best (minimum) value for each single attribute among all alternatives. In other words, the minimum value in the rows fixing the column in matrix (2). Keeping the numerical example reported above, the utopia vector for the sensor n at the time t selects the packet loss rate from choice 1 and the average packet delay from choice 2. In short: ${}^{id}A^n(t) = [0.5, 0.813]$.

Among the J alternatives, the SES selection algorithm chooses the SES called $j_{opt}^n(t)$, which minimizes the distance, in term of Euclidean Norm, with the ideal alternative:

$$j_{opt}^n(t) = \left\{ j^n = \arg\min_{j\in[1,J]} \left\| A_j^n(t) - {}^{id}A^n(t) \right\|_2 \right\}, \forall k \in [1, K] \quad (5)$$

It allows getting the Selection Vector (SV) in (6).

$$SV(t) = \left[j_{opt}^1(t), ..., j_{opt}^n(t), ..., j_{opt}^N(t) \right] \quad (6)$$

The described SES selection algorithm is called *Minimum Distance with Utopia Point (MDUP)*. Using the numerical example again: $\left\| A_1^n(t) - {}^{id}A^n(t) \right\|_2 = \sqrt{(0.5-0.5)^2 + (1-0.813)^2} = 0.187$ and $\left\| A_2^n(t) - {}^{id}A^n(t) \right\|_2 = \sqrt{(1-0.5)^2 + (0.813-0.813)^2} = 0.5$. $j_{opt}^n = 1$: all the packets coming from the sensor n will be forwarded only by SES 1.

From the operative viewpoint, after performing the computation in (5) at the time $t = \left\{ t_{D,h}^{(n)}, h \in \mathbb{N} \right\}$, the generic $DM^{(n)}$ communicates the decisions to each SES. For example it can transmit the vector $SV(t)$ from which each SES can read the source sensor whose information must be forwarded or not. The source sensor is recognized in each SES by using a specific field in the packet header. Considering the j-th SES and the sensor n as source of the received packets, the algorithm works as follows for the period of time when $SV(t)$ is valid: at each received packet, if $(j = j_{opt}^n)$ then the packet is forwarded to the satellite link by the SES j, otherwise the packet is dropped by it. The computation of the attributes for the decision is a topical point. The metric measures are taken at the RMH, where also DMs are located for the sake of simplicity, so to fill the matrix (2) and the vector (3). Attribute values $\left[X_{j1}^n, ..., X_{jk}^n, ..., X_{jK}^n \right]$ are collected through periodic measure phases of length $T_{M,h}^{(n)}, n \in [1, N], h \in \mathbb{N}$ for each sensor during which the packets coming from the sensor n are forwarded through all J SESs. During the measure phase for the sensor n, each SES receives the packets from the sensor n and forwards them to the satellite link. The time relation between measure phases and decision instants is shown in Fig. 2. Measure phases are kept separate for each single sensor n. This is a design choice. The measure phases of different sensors may be also overlapped, paying attention to limit the interference with regular traffic, which is introduced by the measure phases. Consecutive measures for single sensors followed by related decisions, as in Fig. 2, guarantee to limit the traffic interference during the measure phases to a minimum. The drawback may be the length of the period $T_{D,h}^{(n)}, n \in [1, N]$, where the decision taken in $t_{D,h}^{(n)}$ is valid for the sensor n. It may impact on the reaction of the algorithm to sudden traffic changes. Moreover, single $T_{M,h}^{(n)}$ must be long enough to assure reliable measures. The trade-off between traffic interference, fast reaction to traffic changes, and measure reliability will be the object of future performance evaluation. It is not investigated here for the sake of brevity. Even if the formal approach presented above is not linked to a specific choice of attributes, the set of selected metrics for this letter is: *Packet Loss Rate (PLR)*, which is the ratio between lost and sent packets. $PLR_j^{(n)}(t)$ is the value of this attribute, valid at the time t, for the sensor n, when packets flow through SES j. In short, $PLR_j^{(n)}(t) = X_{j1}^{(n)}(t)$. *Average Packet Delay (APD)*, which is the average time a packet needs to go from the source sensor to the RMH destination. Similarly as for the previous case: $APD_j^{(n)}(t) = X_{j2}^{(n)}(t)$. *Average Energy (AE)*, which is the energy state of the path followed to propagate the packets from the source to the destination. At the start a packet stores the energy spent by the source sensor to transmit packet up to that time. When the packet arrives at the next sensor (if any) or, alternatively, at the SES, as in Fig. 1, it detects the energy spent by it up to that time, sums the amount to the stored value, and memorizes the result. The procedure is iterated up until the destination. The energy measures carried by each packet for a given sensor n and a given alternative j are averaged together. Each packet broadcasting is assumed to use 1 [mJoule]. $AE_j^{(n)}(t) = X_{j3}^{(n)}(t)$. For the peculiar

TABLE I
COMPARISON OF SES SELECTION METHODS.

	MDUP	*Static*	*PLR-opt*	*APD-opt*	*AE-opt*
APD [ms]	**329.8**	337.6	303.9	*282.3*	379.3
PLR [%]	**11.17**	24.31	*1.16*	20.36	57.46
AE [mJoule]	**31371**	26714	33145	33423	*17459*

network topology where the same packet generated by a given sensor is directly received by all SESs so providing the same information to all of them, the energy state of the path before reaching the SES has no impact on *AE* attribute. Only the energy at SES varies and is considered in this letter. From the practical viewpoint the following information must be contained in the packet header to allow the collection of the measures: sequence number and time stamps to measure *PLR* and *APD*; energy spent in the path to measure *AE*. A global clock to align time stamps is supposed available throughout the network.

III. SES PERFORMANCE EVALUATION

Simulations are carried out through an ad-hoc *C++* tool. The duration of the simulations is set to 300 [s]. The radio channel is considered ideal. Its bandwidth is 100 [Kb/s]. The propagation delay between sensors and SESs is 30 [s]. Each packet is 1000 [bit] long. The buffer size through which each SES is modeled is 20000 [bit]. N=20. Each sensor generates packets through a Poisson probability distribution whose average value is 20 [packets/s]. J=4. SES 1, 2, and 4 has a bandwidth availability of 125 [Kb/s]; SES 3 of 31.25 [Kb/s]. The bandwidth availability may vary over time but it is kept fixed here for the sake of simplicity. The satellite channel is modeled through an independent identically distributed (i.i.d) model: in practice for each bit there is error probability (Bit Error Ratio - *BER*) independent of other bits but identical for each of them. *BER* is set to 10^{-3} for SES 4 and to 0 (ideal channel) for all other stations. The propagation delay from each SES to RMH is 260 [ms]. $T_{D,h}^{(n)}$=20 [s], $\forall n$, $\forall h$. $T_{M,h}^{(n)}$=1 [s], $\forall n$, $\forall h$.

The *MDUP* selection method is compared with four other schemes. The first one is called *Static* and equally distributes the sensor traffic independently of the channel bandwidth and state. In practice, each SES forwards the packets of 5 predefined sensors. The other ones belong to the family of mono-attribute scheme. They use the same optimization criterion defined in Section II but applied only for a single attribute: *PLR-opt* optimizes only *PLR*, *APD-opt* only *APD* and *AE-opt* only *AE*. The test scenario is aimed at evaluating the performance when there are satellite bandwidth unbalance, which mainly affects delay, and channel corruption, which mainly affects losses, in the same time. Table I contains the results. The algorithms optimized for a single attribute obviously provide the best results for that metric, which are reported in Italics in Table I. Excellent performance for one metric is paid by reduced performance in other metrics. The combination *APD*=282.3 [ms], *PLR*=1.16% and *AE*=17459 [mJoule] is the ideal performance which would be provided by the *Utopia point*. The aim of *MDUP* is to approach the ideal performance as close as possible. The macroscopic result is that *MDUP* is a good compromise among the single attribute techniques and provides numerical values for the metrics so to assure usability in real systems. For example, concerning *PLR*, all solutions provide values above 20% hardly usable in the field, except for *PLR-opt* (1.16%) and *MDUP* (11.17%). On the other hand *PLR-opt* gets larger *AE* values than *MDUP*. *AE* is a very critical parameter: decreasing *AE* implies a big increase of the other metrics, as clear for *AE-opt* and for *Static*. Additionally *MDUP* has also a positive side effect for *AE*. While *PLR-opt* implies a large *Standard Deviation (sd)* of the SES *AE* values, *MDUP* assures a lower *sd* value. The *AE* values in [mJoule] at each SES for *PLR-opt* are: 63266 for the SES 1; 53649 for the SES 2; 10092 for the SES 3; and 5575 for the SES 4. The *Standard Deviation* is 25589. The *AE* values at each SES for *MDUP* are: 47172 for the SES 1; 46385 for the SES 2; 16852 for the SES 3; and 15077 for the SES 4. The *Standard Deviation* is 15422 [mJoule]. *MDUP* distributes the energy consumption among SESs more fairly than *PLR-opt*, which tends to concentrate the energy consumption in SESs that have more favorable bandwidth and *BER* conditions (SES 1 and SES 2). It may have consequences on SES lifetime.

IV. CONCLUSIONS

MDUP is aimed at minimizing the distance with an ideal situation for a set of metrics possibly contrasting each other. It allows obtaining satisfying numerical results for *APD* and *AE*. It also assures *PLR* values that can still guarantee practical operability for the communication between sensors and RMH.

REFERENCES

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