Energy-Efficient Routing in Mobile Wireless Sensor Networks using Mobility Prediction

Andrea Munari†, Wolfgang Schott†, and Sukanya Krishnan∗
† IBM Research GmbH - Zurich Research Laboratory (ZRL), Zurich, Switzerland
∗ Networked Systems Laboratory, EPFL, Lausanne, Switzerland
email: {una, sct}@zurich.ibm.com, sukirish@gmail.com

Abstract—A method is presented for efficiently and reliably routing data packets from a static information source to a mobile sink through a multi-hop wireless sensor network. While the source and all sensor nodes are located at fixed and known positions, the mobile sink estimates and tracks its location, speed, and acceleration with a Kalman filter. To reliably and timely route data packets, the source predicts the location of the mobile sink. The prediction is updated by receiving messages from the mobile sink, containing its current location, speed, and acceleration. These messages are sent only if the Euclidean norm of the error between the predicted state and the state estimated by the Kalman filter exceeds a pre-defined threshold. The control messages and the data packets are forwarded in a multi-hop fashion through the network using geographic routing. Simulation results demonstrate that the proposed scheme outperforms conventional routing protocols in terms of packet transfer reliability, latency, and energy efficiency.

Keywords: Mobile WSN, geographic routing, localization

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are typically composed of a large number of battery powered and computationally limited sensor nodes that are scattered over a wide geographic area. In many WSN applications, the sensors form an ad hoc network to route data from an information source to one or several sinks in a multi-hop fashion. For this purpose, static routing protocols such as AODV [1] or DSR [2] are often applied that rely on the construction of a single routing path from the source to the sink before forwarding data.

In recent years, novel location-based services have created a growing interest in the design of wireless sensor networks with mobile sinks, i.e. mobile WSNs. In [3], for example, the authors consider a scenario in which multiple users equipped with mobile phones move through a sensor field and interact with a WSN by querying information of interest. In [4], a similar application has been described for a "store of the future", where customers receive local advertising and product information on their shopping-cart tablet via a WSN from a central server. Another example of a mobile WSN has been described for an intelligent transportation system in [5]. In this case, mobile sinks are represented by cars that collect updates from static sensors about traffic conditions and potential environmental dangers.

However, the presence of mobile sinks in a WSN may introduce frequent changes of the network topology, which makes it difficult to establish and maintain a stable and reliable routing path in case of using static protocols. Whenever a route is broken due to sink mobility, route recovery messages have to be exchanged to build a new path. This approach significantly increases the overhead and thus degrades the network performance in terms of latency and energy consumption. These disadvantages can be alleviated by using a dynamic protocol such as geographic routing [6] to forward the data packets. This protocol does not require the execution of a route construction procedure before transmitting data, but it assumes that each node knows its own geographic location and the position of the destination. A sensor node that has data to forward simply broadcasts a request packet with the geographic coordinates of the sink to its neighbors. The receivers of this message exploit their topological knowledge to calculate the advancement they can offer towards the sink and contend among each other to elect the next hop closest to the destination. The capability of geographic routing to avoid route construction, however, comes at the expense of tracking the destination. To unleash the potential of this approach, it is thus fundamental to design an efficient strategy to continuously monitor the geographic position of the sink and distribute this information in the network.

Starting from these remarks, in this paper we present a novel geographic routing protocol for efficiently and reliably forwarding data packets from a static information source to a mobile sink through a multi-hop wireless sensor network. While the source and all sensor nodes are located at fixed and known positions, the mobile sink estimates and tracks its state (i.e. its location, velocity, and acceleration) from noisy measurements with a Kalman filter. To reliably and timely route data packets, the source predicts the location of the mobile sink. The state of the predictor is updated by receiving STATE-UPDATE messages from the mobile sink, which contain its current state. These messages are not periodically sent, but only if the Euclidean norm of the error between the predicted state and the state estimated by the Kalman filter exceeds a pre-defined threshold. The STATE-UPDATE messages as well as the DATA packets are forwarded in a multi-hop fashion through the wireless sensor network using geographic routing. Our simulation results demonstrate that the proposed scheme outperforms conventional routing protocols in terms of packet transfer reliability, latency, and energy efficiency.

The paper is outlined as follows. Section II discusses the related work. Section III introduces our approach to routing in
mobile WSNs. Section IV describes the method for estimating and tracking the state of the mobile sink, and its prediction at the source. Details on the proposed geographic protocol are given in Section V. Section VI provides the simulation results followed by our conclusions in Section VII.

II. RELATED WORK

Several solutions for fast and reliable data delivery to mobile sinks in a WSN have been proposed in the literature. Most of them incorporate routing protocols that have originally been designed for static ad hoc networks and exploit the concepts of clustering and mobility prediction.

In [7], a two-tier data dissemination model for large-scale WSNs has been proposed. The main idea of this approach is to partition the WSN into clusters, each of them with a clusterhead that knows a route back to the source. Whenever a mobile sink enters the sensor field, a local flooding procedure is triggered to inform the clusterhead of its presence. The node then forwards the query of the sink to the source along the known route. Once the source has received the query, data packets can be transmitted to the mobile sink following again a two-tier approach: packets follow known and static routes up to the clusterhead that has in turn the role to forward them to the sink coping with its mobility. The advantage of this approach over classical AODV and DSR routing is that the flooding of messages is kept local and only quick adjustments to the path have to be made as long as the sink moves within the cluster. However, it should be noted that flooding is not completely avoided and still has a severe impact on the network performance if the sink moves from one cluster to another.

In [5], a simple yet effective routing solution has been proposed that enhances the two-tier dissemination protocol of [7] by incorporating mobility prediction. The authors consider a WSN deployed along a street to gather environmental data and route the collected information to cars passing by. The cars (i.e. the mobile sinks) are equipped with a GPS based positioning system and are thus aware of their location, speed, and mobility pattern. When a car enters the WSN, it sends out an information query to a sensor next to the road, containing its speed and trajectory, and indicating the region from where it wants to receive the requested environmental information. When a sensor receives the query, the request is forwarded by means of a geographic routing protocol to the sensor node that is closest to the center of the indicated region. This node takes on the role of a clusterhead and initiates gathering of local environmental information. Once the procedure is accomplished, the clusterhead aggregates the collected data and forwards the generated packet to the car at the predicted location. The proposed scheme is tailored to a specific application that is relevant for the automobile industry. However, its improvements cannot easily be achieved in an indoor environment because GPS cannot be applied.

In [8], the authors propose to enhance the performance of a vehicular ad-hoc network by embedding an adaptive beaconsing strategy into the geographic routing protocol GPSR [9]. To reduce the overhead in the network, the frequency of beacon transmissions containing the geographic location of the mobile sinks is adapted to the node mobility and the network traffic. In [8], however, no method is described how routing can be efficiently combined with a location tracking scheme. On the contrary, in [4] a method is described for efficiently sensing and tracking slowly moving objects in an indoor environment but no information is provided on how data can be routed to them.

III. GEOGRAPHIC ROUTING IN MOBILE WSNs

In order to introduce the key ideas of our proposal, let us consider the scenario depicted in Fig. 1, composed by a set of static wireless sensor nodes \( \{s_i\} \) deployed at known geographic positions, a mobile sink MS that moves with a time-varying speed \( v(t) \) along an unknown trajectory \( r(t) \) through the sensor field, and a source S that is located at a known position. The source has one or several DATA packets to transmit to the MS. In general, such frames cannot be directly transmitted to the destination over a single radio link because the MS is often too far away; therefore, multi-hop transmissions have to be applied.

An efficient solution for forwarding a DATA packet hop-by-hop from the source to the mobile sink can be obtained by applying geographic routing. This approach does not establish a static path from S to MS before transmitting data, but it rather dynamically establishes a route while forwarding the information. In particular, when a data packet for the sink is generated, the source selects the node among its neighbors which offers the maximum geographic advancement towards the MS. Once the next hop is chosen, the DATA packet is forwarded to the selected node that, in turn, iterates the procedure until the sink is reached.

Geographic routing can only be applied if all sensor nodes are aware of their geographic location as well as the position...
To achieve the latter goal, the MS has to transmit this information has to be distributed in the network. To achieve the latter goal, the MS has to continuously monitor its position, while on the other hand this information has to be distributed in the network. In order to achieve this, two tasks have to be accomplished: on the one hand, a mobile node has to inform S about the current position of the destination. In this paper, we propose a novel protocol that uses the Singer acceleration model [10]. The position of the sink. However, while in this scenario the former condition can easily be met, the mobility of the sink creates the need for a mechanism to inform S about the current position of the destination. In order to achieve this, two tasks have to be accomplished: on the one hand, a mobile node has to continuously monitor its position, while on the other hand this information has to be distributed in the network.

The next two sections describe in further details our approach to effectively fulfill the two goals.

IV. STATE ESTIMATION AND MOBILITY PREDICTION ALGORITHMS

The mobile sink estimates its geographic location with a Kalman filter that monitors noisy position measurements obtained with sensor devices such as accelerometers, gyroscopes, compass, etc. [4]. The design of the Kalman filter is based on a state-space model that describes a random movement of the MS along one axis of the coordinate system and ignores imperfections of the measurement device. The extension to a more complex, but more accurate model and to a multidimensional coordinate system is straightforward.

Let us assume that the mobile sink moves along a trajectory $r(t)$ that is a straight line parallel to one axis of the coordinate system. Initially, the MS is stationary at position $r(0) = 0$. For time $t \geq 0$, the MS is driven by a random acceleration $a(t)$ that is modeled by a first-order Markov process

$$a(t) = -\alpha a(t) + w(t), \quad \alpha \geq 0, \quad (1)$$

where $w(t)$ represents white noise with variance $\sigma_w^2 = 2\alpha \sigma_a^2$ and $\alpha$ is reciprocal to the time maneuver constant of the mobile sink. The movement of the MS can thus be modeled by setting the parameters $\alpha$ and $\sigma_a^2$. Typical values can be obtained from the Singer acceleration model [10]. The position $r(t)$ of the MS relates to its acceleration $a(t)$ according to the Newton law

$$\ddot{r}(t) = \dot{v}(t) = a(t), \quad (2)$$

where $v(t)$ denotes the MS velocity.

The linear differential equations (1) and (2) represent the continuous-time system model of the investigated system and can be written in the state-space form

$$\dot{x}(t) = Fx(t) + Gw(t), \quad (3)$$

where the state vector $x(t)$ and the matrices $F$ and $G$ are defined as:

$$x(t) = \begin{bmatrix} r(t) \\ v(t) \\ a(t) \end{bmatrix}, \quad F = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\alpha \end{bmatrix}, \quad G = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}. \quad (4)$$

The corresponding discrete-time system model is given by

$$x_{k+1} = \Phi x_k + u_k, \quad (5)$$

as shown in Fig. 2, where the elements of the state vector $x_k^T = [r_k \ v_k \ a_k]$ represent samples of the position, velocity, and acceleration of the MS at time $kT$. The matrix $\Phi$ defining the transition between two successive states is given by

$$\Phi = \begin{bmatrix} 1 & T & 1/2T \\ 0 & 1 & 1/2 \\ 0 & 0 & e^{-\alpha T} \end{bmatrix}. \quad (6)$$

$u_k$ is a discrete-time white noise vector with covariance matrix

$$Q = E\{u_k u_k^T\} = 2\alpha \sigma_a^2 \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{12} & q_{22} & q_{23} \\ q_{13} & q_{23} & q_{33} \end{bmatrix}. \quad (7)$$

whose coefficients are reported at the bottom of next page.

Moreover, we assume that the location position $r_k$ embedded in additive white noise can be measured at the output of the system. The discrete-time measurement model is thus given by

$$z_k = Hx_k + n_k \quad (8)$$

as illustrated in Fig. 2, where the matrix is given by $H = [1 \ 0 \ 0]$ and $n_k$ is additive white noise with variance $\sigma_n^2$.

Based on the discrete-time state-space model given by (5) and (8), the optimal Kalman filter can be derived [11]. As
shown in Fig. 3, this filter monitors the noisy measurements $z_k$ at the MS and computes in real-time a state estimate $\hat{x}_k^T = [\hat{r}_k \hat{v}_k \hat{a}_k]$ of the MS that comprises the position estimate $\hat{r}_k$, velocity estimate $\hat{v}_k$, and acceleration estimate $\hat{a}_k$. An iterative computation of $\hat{x}_k^T$ is achieved by firstly predicting the state of the MS based on the equation

$$\hat{x}_k = \Phi \hat{x}_{k-1}. \quad (9)$$

The predicted state $\hat{x}_k$ is thus given by linearly projecting the state estimate $\hat{x}_{k-1}$ from time $(k-1)T$ one time interval ahead using the transition matrix $\Phi$. Afterwards, the state estimate error covariance matrix $P_k$ for the current predicted state is calculated using the updated state estimate error covariance matrix $P_{k-1}$ of the previous state estimate $\hat{x}_{k-1}$:

$$P_k = \Phi P_{k-1} \Phi^T + Q. \quad (10)$$

On receiving a location position measurement $z_k$ from the measurement unit at time $kT$, the Kalman filter updates its state estimate based on the equation

$$\hat{x}_k = \hat{x}_{k-1} + \mathbf{K}_k (z_k - H \hat{x}_k). \quad (11)$$

The state estimate $\hat{x}_k$ is thus calculated by adding to the predicted state $\hat{x}_{k-1}$ the error between the location position measurement $z_k$ and the reconstructed output parameter weighted by the Kalman gain vector

$$\mathbf{K}_k = \frac{P_{k-1} H^T (HP_{k-1} H^T + \sigma_n^2)^{-1}}{\sigma_n^2}. \quad (12)$$

To obtain the optimum Kalman filter gain settings, the covariance matrix of the state vector estimation error has to be computed according to

$$P_k = P_{k-1} - \mathbf{K}_k H P_{k-1}. \quad (13)$$

The state estimate $\hat{x}_k$ provided by the Kalman filter is transmitted as parameter of the STATE-UPDATE message from the mobile sink via the sensor field to the source.

The source can thus predict the state $\hat{x}_k$ of the MS according to:

$$\hat{x}_k = \begin{cases} \hat{x}_k & \text{if STATE-UPDATE message has been received at time } kT, \\ \Phi \hat{x}_{k-1} & \text{otherwise.} \end{cases} \quad (14)$$

On receiving a STATE-UPDATE message at time $kT$, the source copies the state $\hat{x}_k$ contained in the message into the register of the state predictor. When no message is received, the source predicts the state of the MS by linearly projecting the predicted state $\hat{x}_{k-1}$ one time interval $T$ ahead using the system matrix $\Phi$. Note that this prediction strategy differs from the one incorporated in the classical Kalman filter. While in the Kalman filter new estimates are obtained immediately after receiving a new measurement $z_k$, the state predictor only takes into account new measurements after receiving an update request from the mobile sink.

To reduce the number of control message exchanges over the WSN, the mobile sink issues a STATE-UPDATE request only if the predicted value $\hat{x}_k$ deviates too far from the state estimate $x_k$ provided by the Kalman filter. To measure this deviation, a copy of the state predictor has also to be implemented at the MS as shown in Fig. 3. The error vector $e_k$ between the state estimate $\hat{x}_k$ provided at the output of the Kalman filter and the predicted estimate $\hat{x}_k$ provided at the output of the state predictor is computed. A comparator calculates the Euclidean norm of the error vector and compares it to a threshold $\varepsilon_{T_h}$. If the norm exceeds $\varepsilon_{T_h}$, the comparator triggers an update of the state of the predictors at the mobile sink and at the source. At the mobile sink, the state estimate $\hat{x}_k$ is directly loaded via the multiplexer into the register of the state predictor. The state of the predictor at the source is updated by transmitting the protocol message STATE-UPDATE with the state estimate $\hat{x}_k$ as parameter.

V. MOBILITY PREDICTION ROUTING PROTOCOL

To effectively implement the routing approach described in Section III and IV, some coordination among nodes is required. In particular, methods to bi-directionally transfer information between a mobile sink and a static source through a WSN have to be provided. To this aim, we present a novel carrier-sense based cross-layer MAC and routing protocol called Mobility Prediction Routing (MPR).

Let us refer to the scenario of Fig. 1 and let us start by considering the situation of a sink that has a notification to send to the source $S$, either because it has just joined the network or because the deviation between predicted and Kalman-filter estimated state has exceeded a threshold. In this case, the mobile station transmits a STATE-UPDATE message containing the current estimate of its state following the standard 802.11 CSMA mechanism based on Binary Exponential Backoff (BEB) [12]. Nodes in $\{s_i\}$ that successfully decode this packet enter a distributed contention procedure to select the node that has to forward the information. To this aim, each candidate evaluates the advancement it offers towards the source 1 and picks an integer $m$ inversely proportional to the computed value in the set $\{1, 2, \ldots, CW - 1\}$, where CW

$$q_{i1} = \frac{1}{2\alpha^5} \left[ 1 - e^{-2\alpha T} + 2\alpha T + \frac{2\alpha^3 e^{-\alpha T}}{3} - 2\alpha^2 T^2 - 4\alpha T e^{-\alpha T} \right]$$

$$q_{i2} = \frac{1}{2\alpha^5} \left[ e^{-2\alpha T} + 1 - 2e^{-\alpha T} + 2\alpha T e^{-\alpha T} - 2\alpha T + \alpha^2 T^2 \right]$$

$$q_{i3} = \frac{1}{2\alpha^3} \left[ 1 - e^{-2\alpha T} - 2\alpha T e^{-\alpha T} \right]$$

$$q_{i22} = \frac{1}{2\alpha^3} \left[ 4e^{-\alpha T} - 3 - e^{-2\alpha T} + 2\alpha T \right]$$

$$q_{i23} = \frac{1}{2\alpha^2} \left[ e^{-2\alpha T} + 1 - 2e^{-\alpha T} \right]$$

$$q_{i13} = \frac{1}{2\alpha} \left[ 1 - e^{-2\alpha T} \right].$$

1We remark that since the source is assumed to be static and location aware, its geographical position can be easily distributed to other nodes in the WSN, e.g., by means of a broadcast procedure, after network deployment.
is a protocol parameter that specifies the contention window for the selection of a next hop. The node, then, starts a backoff of duration $m$ slots and senses the aggregate power level on the medium $P$. If $P$ exceeds the carrier sense threshold $\Lambda_{CS}$, the node assumes that another terminal has won the contention and goes back to its activity. On the contrary, if the backoff interval expires and $P$ remains below $\Lambda_{CS}$, the candidate is selected as data forwarder and replies to the sink with an acknowledgement (ACK) message.\textsuperscript{2}

Once this first hop has been accomplished, basic geographic routing can be performed within the static WSN in order to deliver data to the source. The terminal in charge to forward the STATE-UPDATE message, after a carrier sense based BEB, transmits the packet to its neighbors. Nodes that decode the frame perform the distributed contention described earlier to identify the next hop which is closest to the source, which in turn replies with an ACK and iterates the procedure until the final addressee of the message is reached.

Finally, upon receiving a STATE-UPDATE message from a sink, the source can start processing packets addressed to it. In particular, when a data frame has to be delivered to a mobile node, S applies the algorithm described in Section IV to predict the current location of the addressee. This information is then included in the packet and the aforementioned geographic routing procedures take place to deliver data to the sink through the static WSN.

\section{VI. Simulation Results}

In order to test the effectiveness of the proposed solution, extensive Omnet++ \cite{13} simulations have been performed. In our studies, we have considered wireless sensor networks composed by 36 static nodes spread in a 6×6 regular grid over a 100×100 m$^2$ area and by one or more sinks moving within the region. The motion of the nodes has been modeled as discussed in Section IV. In particular, the reciprocal of the maneuver time, $\alpha$, has been set to 30 Hz. Such a value is suitable to describe the movement of both pedestrians and human-driven vehicles, and is thus of interest for many potential applications. Poisson traffic addressed to the mobile sinks with intensity $\lambda = 5$ packets/s/sink is injected in the network by a single source, located at the upper-left corner of the grid.

The Mobility Prediction Routing protocol has been compared to two benchmark schemes: AODV and basic geographic routing (Geo). In the latter approach, mobile sinks periodically transmit beacons containing an estimate of their current location. Let us remark that while STATE-UPDATE messages in MPR contain the Kalman filter estimate $\hat{x}_k$, in Geo the raw noisy measurement of the current position $z_k$ are included in beacons. Such frames are forwarded towards the source according to the procedure described in Section V. In turn, whenever a new data packet has to be delivered, the source triggers the plain geographic routing algorithm assuming the addressee to be located at the position indicated in the last received beacon, i.e., no prediction is performed.

All the schemes rely on a carrier sense based medium access policy with BEB. In order to have a fair comparison, we have tuned the Short Retry Limit (SRL) parameter \cite{12} so as to achieve a similar reliability for the different protocols under static conditions (i.e., when sinks are not moving). In particular, the SRL has been set to 5 for AODV, whereas 4 attempts were sufficient for basic geographic routing and MPR, due to the shorter average length of the routes packets have to undergo to reach a sink.

The wireless environment is subject to correlated Rayleigh fading and path loss with coefficient $\beta = 3$. The standard set of network and protocol parameters used in our studies are reported in Tab. I.

MPR and its competitors have been studied in two different scenarios. In the former, a single sink was present in the network, and the behavior of the protocols has been analyzed under different mobility conditions. This was accomplished by varying the parameter $\sigma_a$ (see Section IV), which represents the standard deviation of the acceleration of a sink, and hence gives an indication of how quickly a node can vary its speed and thus its trajectory. This investigation is of particular interest since it sheds light on the robustness of the considered routing policies to user mobility and tests their adequacy to different applications. Furthermore, the protocols have been assessed in networks with multiple sinks sharing the same mobility parameters. Such a scenario is apt to evaluate how the schemes respond to higher traffic loads and how they behave under harsh channel contention conditions.

All the results presented in this paper have been obtained by averaging the outcome of 50 independent simulations, each 1000s long, which provided the desired statistical confidence.

\begin{table}[t]
\centering
\caption{Parameters used in our simulations}
\begin{tabular}{|l|l|}
\hline
Transmission power & 3 dBm \\
Noise floor & -90 dBm \\
Detection threshold & -81 dBm \\
Path loss exponent, $\beta$ & 3 \\
Carrier frequency & 2.4 GHz \\
Bitrate & 250 kbps \\
Reciprocal of maneuver time, $\alpha$ & 0.033 \\
Measurement noise variance, $\sigma_\alpha^2$ & 2 m$^2$/s$^2$ \\
Error detection threshold, $\Delta_{CS}$ & 5 \\
Nominal load per sink, $\lambda$ & 5 pk/s/sink \\
MAC buffer size & 16 \\
BEB Initial contention window & 32 slots \\
Short Retry Limit - AODV, Geo, MPR & 5, 4, 4 \\
Slot, DIFS, SIFS duration & 21, 128, 28 $\mu$s \\
Carrier Sense threshold, $\Lambda_{CS}$ & -86 dBm \\
Contention Window for next hop selection, CW & 16 slots \\
Payload & 512 bit \\
Header, ACK, Control Packets & 42, 96, 112 bit \\
\hline
\end{tabular}
\end{table}

\textsuperscript{2}If the source is able to decode the STATE-UPDATE, it immediately replies with an ACK, i.e., $n_s = 0$, in order to avoid routing procedures that would be useless and expensive in terms of energy consumption.

\subsection{A. Networks with a single mobile sink}

Let us start our analysis by considering the response of the protocols to different mobility conditions when a single sink
Fig. 4. Packet delivery ratio as a function of the standard deviation of the sink acceleration \( \sigma_a \).

is present. The first performance criterion that we assess is the end-to-end Packet Delivery Ratio (PDR), defined as the ratio of the number of data packets injected in the network to the number of frames successfully received at the intended addressee. The metric is depicted against the standard deviation of the sink acceleration \( \sigma_a \) in Fig. 4. As expected, when the mobile user is static or quasi-static (e.g., for low accelerations), all the considered schemes provide a good reliability of about 95%. On the contrary, higher values of \( \sigma_a \) induce a performance loss for the protocols. As for AODV, this can be explained considering the static routing approach it relies on. According to this, a path to the destination is composed by a set of forwarding nodes identified by means of a broadcast-based route discovery procedure. However, as soon as the sink moves out of the communication range of the last node in the identified sequence, the whole route collapses, and data cannot be delivered until a new path to the destination is established through route recovery. Such a condition occurs more often as the value of \( \sigma_a \) increases, with detrimental effects on the overall reliability (up to 10% loss for high acceleration). This drawback can be partially mitigated by applying geographic routing. Indeed, such a strategy can be robust to user mobility provided that sinks send out beacons with position updates with sufficient high frequency. In particular, Fig. 4 highlights that, for the topologies under study, a beacon interval of 1 second leads to a constant reliability for pedestrian or vehicle movement up to moderate speeds, whereas the performance starts to slightly degrade only for higher values of \( \sigma_a \). The improvement offered by geographic routing stems from the capability of the beacons to provide the source with an estimate of the current position of the sink. This knowledge is exploited to track the destination and, unlike in AODV, to pre-emptively adapt the path frames have to undergo, thus reducing the number of packet losses. However, such a strategy is extremely sensitive to the accuracy of the location estimate available at the source. In fact, as soon as this information does not reflect the actual position of the addressee, either due to the loss of some updates or because the beaconing frequency is not high enough with respect to the mobility pattern of the sink, data deliveries fail, since packets are forwarded using an inappropriate route. This is clearly shown in Fig. 4, where the curves for geographic routing with beaconing interval of 3 and 5 seconds plummet as \( \sigma_a \) increases. From these observations we can infer that the robustness against sink mobility that can be achieved by means of basic geographic routing comes at the expense of a high beaconing frequency, which in turn increases overhead and energy consumption in the network, as will be discussed later. Let us now focus, instead, on the MPR protocol. The plot highlights that our scheme offers high PDR for all the considered values of \( \sigma_a \) and is thus able to overcome the issues that affect basic geographic routing. This capability stems from two aspects. First of all, as discussed in Section IV, MPR adapt the beaconing interval to the mobility pattern of the sink. Therefore, the source always has at its disposal an up to date estimate of the destination’s position and can reliably transfer data even for high values of \( \sigma_a \). Secondly, with the proposed strategy, packets for the sink are routed towards the expected current location of the addressee obtained by means of the prediction algorithm rather than towards the position contained in the last received \textit{STATE-UPDATE}, thus handling potential movements of the sink between successive beacons.

The second performance criterion that we consider is transmission energy consumption, which is of key importance in battery constrained WSNs. The metric is defined as the ratio of the transmission energy consumed by all the nodes in the network to the number of successfully received information bits at the sink, and is depicted against the standard deviation of the acceleration in Fig. 5. Let us start by focusing on the behavior of the different protocols for low values of \( \sigma_a \), i.e., when all the schemes offer the same level of reliability, as shown in Fig. 4. As a first remark, we notice that AODV consumes less energy than basic geographic routing. In such conditions, sink mobility seldom induces failures in the paths...
established by AODV, and therefore the overhead related to route construction and route recovery is limited. On the contrary, the periodic beaconing approach followed by the geographic routing solution enforces the network to process control messages even when not needed because the sink is not moving, and thus yields a higher energy consumption. Remarkable energy savings over both the strategies can be achieved by using MPR: as proven by Fig. 5, our protocol offers improvements of about 15% over AODV and of up to 30% with respect to basic geographic routing. Not only is the proposed solution able to avoid the overhead due to path construction and recovery procedures that affects static routing algorithms, but it also saves energy by triggering STATE-UPDATE messages only when needed in order to preserve reliability. The beneficial effects of MPR become even more pronounced for higher values of $\sigma_a$. Indeed, faster and more dynamic mobility patterns of the sink negatively affect both AODV and geographic routing: the former approach has to face more frequent route failures with a subsequent increase in the control traffic overhead, while the latter schemes undergo a steady drop in reliability and thus tend to spend more energy to successfully deliver a packet to the sink. Instead, MPR exhibits just a slight raise in energy consumption even in such harsh conditions for routing protocols. This stems once again from the capability of the proposed solution to minimize the traffic required to reliably track the sink by matching the frequency of STATE-UPDATE transmissions to the actual movement pattern of the mobile station.

In conclusion, by jointly considering the results of Figs. 4 and 5, we can infer that the MPR protocol is able to offer both higher reliability and significantly reduce energy consumption, thus prolonging network lifetime, with respect to other conventional routing solutions for mobile WSNs, and thus appears to be a suitable solution for a large number of application scenarios.

B. Networks with multiple mobile sink

We have also tested the behavior of MPR and its competitors in networks with multiple sinks sharing the same mobility parameters. In this study, the standard deviation $\sigma_a$ of the acceleration has been set to 4 m/s$^2$. Such a value describes a pedestrian movement, and is thus of interest for many potential applications, e.g., [4].

The first metric that we consider is the average end-to-end packet delivery ratio, depicted against the number of mobile sinks in the network in Fig. 6. As a general remark, we notice that all the schemes incur a performance loss when more destinations have to be served. Indeed, not only does a larger number of sinks involve a higher network load in terms of data packets that have to be delivered, but it also augments the control traffic needed to establish and keep a connection with the mobile nodes. In turn, this traffic growth leads to a harsher channel contention and to an increased interference level, thus worsening the link reliability and the end-to-end PDR. It is also interesting to observe how this effect is more pronounced for basic geographic routing than for AODV. This can be explained considering the low sink mobility in our simulations. As discussed earlier, in these conditions AODV does not experience frequent route failures. Therefore, once a path towards a destination has been established (via a broadcast-based route construction procedure), further control traffic is not likely to be triggered often. On the contrary, the beaconing approach followed by geographic routing continuously pours control messages in the network even when not necessary, e.g., because a sink is standing still, thus leading to a quicker traffic congestion. Clearly, the higher the beacon frequency, the more detrimental this effect. As opposed to its competitors, MPR exhibits a more graceful degradation of the network performance, as shown in Fig. 6, where our protocol achieves a PDR higher than 90% even when more than 10 sinks are present and outperforms AODV by almost 10% and basic geographic routing by as much as 20%. This remarkable result is once again due to the ability of the proposed solution to both avoid route construction procedures and minimize the number of STATE-UPDATE messages generated by each mobile node, thus significantly reducing the congestion in the network.

Another metric of interest is represented by the average end-to-end latency per successfully delivered data packet, depicted as a function of the number of mobile sinks in the network in Fig. 7. When a single destination has to be served, geographic routing based approaches, i.e., Geo and MPR, are able to almost halve the latency with respect to AODV. This stems from the capability of these schemes to exploit location information to forward data without resorting to the broadcast-based and time consuming route construction procedures that are instead needed by static routing protocols. On the other hand, the higher level of traffic triggered by the presence of multiple sinks in the network increases the delivery delay for all the schemes, due to both the longer average backoffs required to access the channel and to longer queuing time spent by packets at each hop. Nevertheless, Fig. 7 emphasizes that MPR is able to contain this performance loss, outperforming AODV by more than 50% (avoidance of route construction
In conclusion, the MPR protocol does not only offer high reliability even when the network has to support a high level of traffic, but also it is able to deliver information to multiple mobile sinks much quicker than its competitors, which makes it particularly suitable for all the applications that have tight constraints in terms of latency.

VII. CONCLUSIONS

In this paper we have presented a novel protocol for efficiently and reliably routing data packets from a static information source to mobile sinks through a multi-hop wireless sensor network. Mobile nodes estimate their state (geographic location, velocity and acceleration) starting from noisy position measurements by means of a Kalman filter, and transfer such information to the source with \textit{STATE-UPDATE} messages. Exploiting this knowledge, the source is able to continuously predict the location of the sink, and geographic routing is performed to efficiently route data packets through the sensor field to the mobile destination. Moreover, in order to minimize the overhead in the network, \textit{STATE-UPDATE} messages are not periodically sent, but only if the Euclidean norm of the error between the predicted state and the state estimated by the Kalman exceeds a pre-defined threshold.

By means of extensive simulations, we have shown that the proposed scheme is robust to both user mobility and the number of mobile sinks that have to be served. The capability of our solution to take advantage of mobility prediction while minimizing the control overhead leads to significant gains over routing strategies that are commonly used in wireless sensor networks in terms of reliability, energy efficiency, and delivery latency.

REFERENCES