# *WiHound*: Target Tracking with ISAC Using EMLSR in Next-Generation IEEE 802.11 WLANs

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***Abstract*—Next-generation IEEE 802.11 wireless local area network (WLAN) amendments have been proposed to support Wi-Fi stations (STAs) and access points (APs). IEEE 802.11be (Wi-Fi 7) features multi-link operation (MLO) with multi-link device (MLD), where the enhanced multi-link single-radio (EMLSR) operation is promising. Also, IEEE 802.11bf launches a sensing capability, paving the way for integrated sensing and communications (ISAC). Pioneering an innovative combination of EMLSR operation and ISAC functionality in this paper, we propose *WiHound*, a novel method for target tracking with ISAC using EMLSR in IEEE 802.11 WLANs. Specifically, we adopt the Kalman filter for target tracking and develop a score-based ISAC decision approach for the AP MLD to decide between sensing and communications within each transmit opportunity (TXOP). For a sensing TXOP, we solve a discrete convex optimization problem based on Cramér-Rao lower bound (CRLB) to select three STA MLDs required in trilateration. Conversely, for a communications TXOP, we develop an efficient fairness-aware STA MLD selection heuristic approach toward weighted proportional fairness. Simulation results confirm the superiority of *WiHound* on striking a balance between sensing and communications. Moreover, we investigate the effect of number of STA MLDs on the sensing performance of *WiHound*.**

***Index Terms*—Enhanced multi-link single-radio (EMLSR), integrated sensing and communications (ISAC), tracking, Cramér-Rao lower bound (CRLB), weighted proportional fairness**

## I. Introduction

Wi-Fi has been a popular wireless local area network (WLAN) technology ubiquitously deployed all over the world, and its global economic value is envisioned to reach 5 trillion USD by 2025 [1]. With an increase in traffic demand and diverse applications, next-generation IEEE 802.11 WLAN amendments have been proposed to provide essential support.

To tackle the intense traffic demand, the IEEE 802.11be extremely high throughput (EHT) amendment (commercialized as Wi-Fi 7) creates several features [2]. A key feature in IEEE 802.11be is multi-link operation (MLO) [3], [4], which brings in the multi-link device (MLD) architecture that allows stations (STAs) and access points (APs) to operate over multiple links. An STA MLD or an AP MLD hosts multiple interfaces, where each interface has its own link(s) and transmit opportunity (TXOP) through the channel at a specific frequency band. Among various types of MLO, the most promising option is the enhanced multi-link single-radio (EMLSR) operation, which requires less hardware installation [5], [6].

Besides the communications paradigm, the IEEE 802.11bf amendment equips Wi-Fi with a sensing capability, which leads to more versatile Wi-Fi [7]. In IEEE 802.11bf, an AP or an STA (including an interface of AP MLD or STA MLD) acts as a sensing initiator (SI) or a sensing responder (SR), where the SI initiates a sensing procedure with the SR involved for a sensing application. With the communications paradigm and sensing capability, integrated sensing and communications (ISAC) is a promising direction for Wi-Fi [8], [9].

For IEEE 802.11 WLANs, the sensing and communications performance of ISAC can be further improved through EMLSR. To the best of our knowledge, an innovative combination of EMLSR operation and ISAC functionality, supported by IEEE 802.11be and IEEE 802.11bf, respectively, has not been explored in the existing literature of Wi-Fi.

Therefore, in this paper, we propose *WiHound*, a novel method for target tracking with ISAC using EMLSR in IEEE 802.11 WLANs as a pioneering work. In *WiHound*, we adopt the Kalman filter [10] with measurements obtained from trilateration for target tracking and develop a score-based ISAC decision approach for the AP MLD to decide between sensing and communications within each TXOP under an EMLSR operation. For a sensing TXOP, we solve a discrete convex optimization problem with a trilateration performance metric based on Cramér-Rao lower bound (CRLB) [11] to select three STA MLDs required in trilateration. Conversely, for a communications TXOP, we develop an efficient fairness-aware STA MLD selection heuristic approach to a unique knapsack problem [12] with an objective toward weighted proportional fairness [13] which considers both throughput and fairness.

The remainder of this paper is organized as follows. We describe the system model and problem formulation in Sec. II. In Sec. III, we introduce *WiHound* with a detailed overview. We cover the simulation settings and results in Sec. IV. Finally, Sec. V concludes the paper.

*Notations:* Boldfaced capital and lowercase letters denote matrices and column vectors, respectively. Given a vector $\mathbf{u}$, we use $\mathrm{diag}(\mathbf{u})$ to denote the diagonal matrix containing $\mathbf{u}$ on its diagonal. Given a matrix $\mathbf{A}$, we denote $\mathrm{Tr}\{\mathbf{A}\}$, $\mathbf{A}^T$, and $\mathbf{A}^{-1}$ its trace, transpose, and inverse, respectively. For any matrices $\mathbf{A}$ and $\mathbf{B}$, we use $\mathbf{A} \otimes \mathbf{B}$ to denote their Kronecker product. We define $\mathbf{I}_p$ to be the $p \times p$ identity matrix and use $\mathbf{S}^p_{++}$ to denote the set of symmetric positive definite $p \times p$ matrices. For any set $\mathcal{A}$, we use $[\mathcal{A}]^p$ to denote its $p$-subsets. We denote the multivariate normal distribution with mean vector $\mu$ and covariance matrix $\mathbf{\Phi}$ as $\mathcal{N}(\mu, \mathbf{\Phi})$.

## II. System Model and Problem Formulation

In this section, we present the system model and problem formulation of target tracking with ISAC using EMLSR in IEEE 802.11 WLANs.

Consider a Wi-Fi network composed of an AP MLD, $M$ STA MLDs, and a moving target (to be tracked) on a 2D area, where every MLD owns $L$ interfaces. Each STA MLD connects its $l$th interface to the $l$th interface of the AP MLD over its $l$th link through the $l$th channel of channel bandwidth $B_l$ at the $l$th frequency band, $l = 1, 2, ..., L$. An illustration of the Wi-Fi network is shown in Fig. 1. Supported by IEEE 802.11be and IEEE 802.11bf, respectively, the Wi-Fi network features both EMLSR operation and ISAC functionality, with uplink (UL) sensing and downlink (DL) communications.

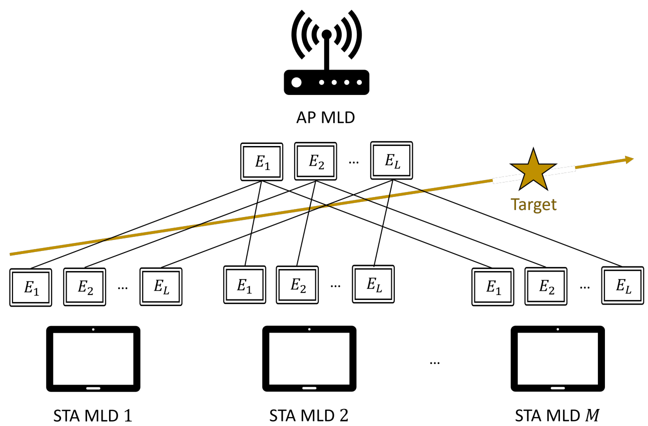
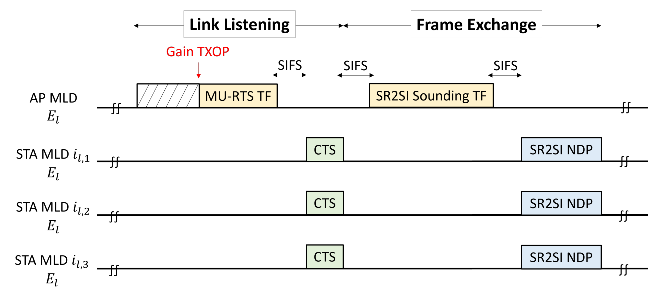


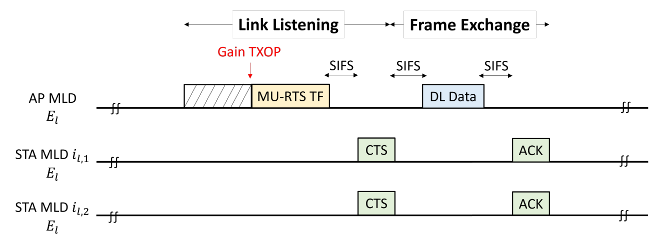

Fig. 1. An illustration of Wi-Fi network, where $E_l$ represents the $l$th interface and each solid line between interfaces represents a link

For EMLSR, define a time window as a period of time of duration $\tau_w$ containing multiple EMLSR operations, where each EMLSR operation occurs between the AP MLD and STA MLD(s) with two phases: link listening and frame exchange. An EMLSR operation begins with the link listening phase. Suppose at time $t$, the $l$th interface of the AP MLD gains a TXOP, and a set of STA MLDs of indices $\mathcal{I}_l^a \subseteq \{1, 2, ..., M\}$ are listening to their $L$ links. For the $m$th STA MLD, $m \in \mathcal{I}_l^a$, denote its position as $(\bar{x}_m, \bar{y}_m)$, the number of its bytes that have been received and to be transmitted DL as $b_m^r$ and $b_m^x$, respectively, and the UL and DL signal-to-noise ratio (SNR) of its $l$th link connected to the AP MLD as $\xi_{m,l}^u$ and $\xi_{m,l}^d$, respectively. Then, the AP MLD selects some STA MLDs of indices $\mathcal{I}_l \subseteq \mathcal{I}_l^a$ to be involved, sending a multi-user request to send (MU-RTS) Trigger frame (TF) from its $l$th interface to the $l$th interface of each STA MLD belonging to $\mathcal{I}_l$. After receiving clear to send (CTS) frames from the STA MLDs, the AP MLD initiates the frame exchange phase. Upon the completion of frame exchange phase, the link listening phase resumes and a new EMLSR operation starts. By the end of a time window, any ongoing EMLSR operation should finish.

With ISAC, the AP MLD decides between sensing and communications under an EMLSR operation when its $l$th interface gains a TXOP at time $t$, given sufficient remaining time in the time window. Suppose by time $t$, the AP MLD has conducted sensing within $N_s$ previous TXOPs (obtaining $N_s$ measurements) and communications within $N_c$ previous TXOPs across its $L$ interfaces. Define a binary variable $\beta$ of value 1 or 0 when the AP MLD intends to conduct sensing or communications, respectively. For the current TXOP at time $t$, the AP MLD needs to generate a predicted state of the target and determine the value of $\beta \in \{0, 1\}$.




(a) UL sensing under EMLSR operation




(b) DL communications under EMLSR operation with $|\mathcal{I}_l| = 2$

Fig. 2. An illustration of ISAC under EMLSR operation

If the AP MLD intends to conduct sensing ($\beta = 1$), then it will experience the $(N_s+1)$th sensing TXOP with UL sensing to obtain a measurement for tracking the corresponding state of the target, expressed as

$$\mathbf{x}[N_s+1] = [x[N_s+1]\,\dot{x}[N_s+1]\,y[N_s+1]\,\dot{y}[N_s+1]]^T, \quad (1)$$

where $(x[N_s+1], y[N_s+1])$ and $(\dot{x}[N_s+1], \dot{y}[N_s+1])$ are the corresponding position and velocity of the target, respectively. Given that the $N_s$th sensing TXOP occurs at time $t'$, the time duration between occurrence of the $N_s$th and $(N_s+1)$th sensing TXOPs is $T' = t - t'$. Then, the target state transition between the $N_s$th and $(N_s+1)$th sensing TXOPs can be expressed with nearly constant velocity (CV) model [14] as

$$\mathbf{x}[N_s+1] = \mathbf{F}\mathbf{x}[N_s] + \mathbf{g}[N_s+1], \quad (2)$$

where $\mathbf{F} = \mathbf{I}_2 \otimes \begin{bmatrix} 1 & T' \\ 0 & 1 \end{bmatrix}$ and $\mathbf{g}[N_s+1] \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_g)$ is the process noise with $\mathbf{Q}_g = g_s \mathbf{I}_2 \otimes \begin{bmatrix} T'^3/3 & T'^2 \\ T'^2 & T' \end{bmatrix}$ of process noise intensity $g_s$. In UL sensing, the AP MLD (with its $l$th interface as SI) involves three STA MLDs (with their $l$th interface as SR) for three range estimates, each of which results from the interaction between the AP MLD and an STA MLD, employing trilateration to obtain a measurement in terms of target position, as illustrated in Fig. 2(a). In the link listening phase, the AP MLD selects three STA MLDs of indices $\mathcal{I}_l = \{i_{l,1}, i_{l,2}, i_{l,3}\} \in [\mathcal{I}_l^a]^3$. Next, in the frame exchange phase, the AP MLD sends an SR2SI Sounding TF to each STA MLD belonging to $\mathcal{I}_l$. After receiving three SR2SI null data packets (NDPs) from the three STA MLDs, the AP MLD derives three range estimates for trilateration to obtain a measurement in terms of target position, written as

$$\mathbf{z}[N_s+1] = \mathbf{H}\mathbf{x}[N_s+1] + \mathbf{v}_{\mathcal{I}_l}[N_s+1], \tag{3}$$

where $\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$ and $\mathbf{v}_{\mathcal{I}_l}[N_s+1] \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_{v_{\mathcal{I}_l}})$ is the measurement noise with $\mathbf{Q}_{v_{\mathcal{I}_l}} = \text{diag}([\sigma^2_{\mathcal{I}_l}\ \sigma^2_{\mathcal{I}_l}]^T)$ of noise variance $\sigma^2_{\mathcal{I}_l}$ dependent on $\mathcal{I}_l$.

If the AP MLD intends to conduct communications ($\beta = 0$), then it will experience the $(N_c+1)$th communications TXOP with DL communications, as illustrated in Fig. 2(b). In the link listening phase, the AP MLD selects some STA MLDs of indices $\mathcal{I}_l = \{i_{l,1}, i_{l,2}, ..., i_{l,|\mathcal{I}_l|}\} \subseteq \mathcal{I}_l^a$. Next, in the frame exchange phase, the AP MLD sends DL data to each STA MLD belonging to $\mathcal{I}_l$, which responds with an acknowledgment (ACK) frame.

Consequently, we formulate the following problem of target tracking with ISAC using EMLSR in IEEE 802.11 WLANs: As the $l$th interface of the AP MLD gains a TXOP under an EMLSR operation with $\mathcal{I}_l^a \subseteq \{1, 2, ..., M\}$ at time $t$, given STA MLD position $\{(\bar{x}_m, \bar{y}_m)\}_{m \in \mathcal{I}_l^a}$, number of bytes that have been received and to be transmitted DL $\{(b_m^r, b_m^x)\}_{m \in \mathcal{I}_l^a}$, and UL and DL SNR of the $l$th link $\{(\xi^u_{m,l}, \xi^d_{m,l})\}_{m \in \mathcal{I}_l^a}$ (with history information from $N_s + N_c$ previous TXOPs), generate a predicted state $\hat{\mathbf{x}}$ of the target and determine the value of $\beta \in \{0, 1\}$ along with indices of selected STA MLDs $\mathcal{I}_l \subseteq \mathcal{I}_l^a$.

## III. *WIHOUND*: Target Tracking with ISAC Using EMLSR in IEEE 802.11 WLANs

In this section, we propose *WiHound*, a novel method for the problem of target tracking with ISAC using EMLSR in IEEE 802.11 WLANs formulated in Sec. II.

### *A. Target Tracking and ISAC Decision*

From Sec. II, the AP MLD needs to track the state of the target and make a decision between sensing and communications within each TXOP under an EMLSR operation.

For target tracking, we adopt the Kalman filter [10], which includes two steps: prediction and update. With regard to the target, the AP MLD generates a predicted state (accompanied by prediction mean squared error (MSE) matrix) in the prediction step within each TXOP and an updated state (accompanied by update MSE matrix) in the update step within each sensing TXOP. When its $l$th interface gains a TXOP under an EMLSR operation at time $t$, the AP MLD computes the predicted state of the target (with updated state $\tilde{\mathbf{x}}'$ and update MSE matrix $\tilde{\mathbf{\Delta}}'$ within the $N_s$th sensing TXOP) as

$$\hat{\mathbf{x}} = \mathbf{F}\tilde{\mathbf{x}}' = [\hat{x}\ \hat{\dot{x}}\ \hat{y}\ \hat{\dot{y}}]^T, \tag{4}$$

where $(\hat{x}, \hat{y})$ and $(\hat{\dot{x}}, \hat{\dot{y}})$ are the predicted position and velocity of the target, respectively, accompanied by prediction MSE matrix $\hat{\mathbf{\Delta}} = \mathbf{F}\tilde{\mathbf{\Delta}}'\mathbf{F}^T + \mathbf{Q}_g$. If the AP MLD intends to conduct sensing ($\beta = 1$) and obtains a measurement $\mathbf{z}[N_s+1]$ within the $(N_s+1)$th sensing TXOP, then it will compute the updated state of the target as

$$\tilde{\mathbf{x}} = \hat{\mathbf{x}} + \mathbf{K}(\mathbf{z}[N_s+1] - \mathbf{H}\hat{\mathbf{x}}), \tag{5}$$

where $\mathbf{K} = \hat{\mathbf{\Delta}}\mathbf{H}^T(\mathbf{Q}_{v_{\mathcal{I}_l}} + \mathbf{H}\hat{\mathbf{\Delta}}\mathbf{H}^T)^{-1}$ is the Kalman gain matrix, accompanied by update MSE matrix $\tilde{\mathbf{\Delta}} = (\mathbf{I}_4 - \mathbf{K}\mathbf{H})\hat{\mathbf{\Delta}}$. Thus, the AP MLD generates predicted state $\hat{\mathbf{x}}$ with (4) at time $t$ and updated state $\tilde{\mathbf{x}}$ with (5) if conducting sensing ($\beta = 1$).

For a decision between sensing and communications, we develop a score-based ISAC decision approach, as illustrated in Algorithm 1. At time $t$, denote the time elapsed from the completion of the $N_s$th sensing TXOP and the time remaining in the current time window as $\tau_1$ and $\tau_2$, respectively. When its $l$th interface gains a TXOP under an EMLSR operation, the AP MLD requires a minimum time $\tau_{s,min} = 3\tau_{SIFS} + 2\tau_{TF} + \tau_{CTS} + \tau_{NDP}$ to conduct UL sensing (from Fig. 2(a)) and a minimum time $\tau_{c,min} = 3\tau_{SIFS} + \tau_{TF} + \tau_{CTS} + \tau_{NDP} + \tau_{ACK}$ to conduct DL communications (from Fig. 2(b)), where $\tau_{SIFS}$, $\tau_{TF}$, $\tau_{CTS}$, $\tau_{NDP}$, and $\tau_{ACK}$ are the time duration of short interframe space (SIFS), TF transmission, CTS transmission, NDP transmission, and ACK transmission, respectively. If the set $\mathcal{I}_l^a$ is non-empty and the remaining time $\tau_2$ is no less than $\tau_{min} = \max\{\tau_{s,min}, \tau_{c,min}\}$, then the AP MLD starts to make an ISAC decision, i.e., determine the value of $\beta \in \{0, 1\}$. For the current $(N_s + N_c + 1)$th TXOP, we compute the distance between the predicted target position $(\hat{x}, \hat{y})$ in (4) and the measured target position within the $N_s$th sensing TXOP $\mathbf{z}[N_s] = [z_x\ z_y]^T$ as $\delta_{N_s+N_c+1} = \sqrt{(\hat{x} - z_x)^2 + (\hat{y} - z_y)^2}$ and the expected sum of rate as $\phi_{N_s+N_c+1} = \sum_{m \in \mathcal{I}_l^a} \bar{B}_l \log_2(1 + \xi^d_{m,l})$, where $\bar{B}_l = B_l / |\mathcal{I}_l^a|$. Denote the counterparts for the $n$th TXOP as $\delta_n$ and $\phi_n$, respectively. Then, we normalize $\delta_{N_s+N_c+1}$ and $\phi_{N_s+N_c+1}$ into their empirical cumulative distribution function (eCDF) value $\bar{\delta}$ and $\bar{\phi}$ (compared with $\{\delta_n\}_{n=1}^{N_s+N_c+1}$ and $\{\phi_n\}_{n=1}^{N_s+N_c+1}$), respectively. Define a control variable $\alpha \in (0, 1)$ for a tradeoff between sensing and communications, where a large $\alpha$ value favors sensing and a small $\alpha$ value favors communications. As a larger value of $\tau_1$ and $\bar{\delta}$ encourages sensing more (due to decreased fidelity of last measurement) and a larger value of $\tau_2$ and $\bar{\phi}$ encourages communications more (due to increased capability for data transmission), we define the sensing score and communications score as

$$(\theta_s, \theta_c) = (\alpha \cdot \tau_1 \cdot \bar{\delta}, (1 - \alpha) \cdot \tau_2 \cdot \bar{\phi}). \tag{6}$$

Finally, we obtain

$$\beta = \mathbf{1}_{\{|\mathcal{I}_l^a| \geq 3 \textbf{ and } \theta_s \geq \theta_c\}}(|\mathcal{I}_l^a|, \theta_s, \theta_c), \tag{7}$$

which is of value 1 (sensing) if $|\mathcal{I}_l^a| \geq 3$ (as trilateration requires three STA MLDs) and $\theta_s \geq \theta_c$ or of value 0 (communications) otherwise.

### *B. STA MLD Selection for UL Sensing*

When the AP MLD intends to conduct sensing ($\beta = 1$), it needs to select three STA MLDs of indices $\mathcal{I}_l = \{i_{l,1}, i_{l,2}, i_{l,3}\} \in [\mathcal{I}_l^a]^3$ for trilateration in UL sensing. Specifically, we quantify the trilateration performance of the AP MLD

**Algorithm 1:** Score-Based ISAC Decision

**Input:** $\mathcal{I}_l^a, B_l, \tau_1, \tau_2, \hat{\mathbf{x}}, \{\xi_{m,l}^d\}_{m\in\mathcal{I}_l^a}, \mathbf{z}[N_s], \{(\delta_n, \phi_n)\}_{n=1}^{N_s+N_c}, \alpha$
**if** $\mathcal{I}_l^a \neq \varnothing$ **and** $\tau_2 \geq \tau_{min}$
  $\delta_{N_s+N_c+1} = \sqrt{(\hat{x}-z_x)^2 + (\hat{y}-z_y)^2}$
  $\bar{B}_l = B_l/|\mathcal{I}_l^a|$
  $\phi_{N_s+N_c+1} = \sum_{m\in\mathcal{I}_l^a} \bar{B}_l \log_2(1+\xi_{m,l}^d)$
  **eCDF normalization:**
  $(\delta_{N_s+N_c+1}, \phi_{N_s+N_c+1}) \xrightarrow{\{(\delta_n,\phi_n)\}_{n=1}^{N_s+N_c+1}} (\bar{\delta}, \bar{\phi})$
  $\theta_s = \alpha\cdot\tau_1\cdot\bar{\delta}$; $\theta_c = (1-\alpha)\cdot\tau_2\cdot\bar{\phi}$
  $\beta = \mathbf{1}_{\{|\mathcal{I}_l^a|\geq 3 \text{ and } \theta_s\geq\theta_c\}}(|\mathcal{I}_l^a|, \theta_s, \theta_c)$
**end if**
**Output:** $(\delta_{N_s+N_c+1}, \phi_{N_s+N_c+1}), \beta$

based on CRLB [11], which indicates the minimum variance of an unbiased estimate. Following the CRLB analysis from [15], we derive the CRLB of range estimate and trilateration estimate in UL sensing (from Fig. 2(a)). As a start, the CRLB of range estimate between the AP MLD and the $m$th STA MLD (with their $l$th interface) can be derived as

$$C_{r_{m,l}} = 3c^2/(8\pi^2\cdot\eta\cdot\omega_l^2\cdot\xi_{m,l}^u), \tag{8}$$

where $c$ is the speed of light, $\eta$ is the number of EHT-long training field (EHT-LTF) repetitions in an SR2SI NDP, and $\omega_l$ is the signaling bandwidth in the $l$th channel. By extending (8), the CRLB of trilateration estimate between the AP MLD and the three STA MLDs of indices $\mathcal{I}_l = \{i_{l,1}, i_{l,2}, i_{l,3}\}$ (with their $l$th interface) can be obtained as

$$C_{t_{\mathcal{I}_l,l}} = \mathrm{Tr}\{\mathbf{\Psi}_{\mathcal{I}_l,l}^{-1}\} = \mathrm{Tr}\{(\mathbf{\Gamma}_{\mathcal{I}_l,l}\mathbf{D}_{\mathcal{I}_l,l}\mathbf{\Gamma}_{\mathcal{I}_l,l}^T)^{-1}\}, \tag{9}$$

where $\mathbf{D}_{\mathcal{I}_l,l} = \mathrm{diag}([C_{r_{i_{l,1},l}}^{-1}\, C_{r_{i_{l,2},l}}^{-1}\, C_{r_{i_{l,3},l}}^{-1}]^T)$ and $\mathbf{\Gamma}_{\mathcal{I}_l,l} = \begin{bmatrix} \frac{x-\bar{x}_{i_{l,1}}}{d_{i_{l,1}}} & \frac{x-\bar{x}_{i_{l,2}}}{d_{i_{l,2}}} & \frac{x-\bar{x}_{i_{l,3}}}{d_{i_{l,3}}} \\ \frac{y-\bar{y}_{i_{l,1}}}{d_{i_{l,1}}} & \frac{y-\bar{y}_{i_{l,2}}}{d_{i_{l,2}}} & \frac{y-\bar{y}_{i_{l,3}}}{d_{i_{l,3}}} \end{bmatrix}$ with $(x,y)$ being the target position and $d_{i_{l,j}} = \sqrt{(x-\bar{x}_{i_{l,j}})^2 + (y-\bar{y}_{i_{l,j}})^2}$ being the distance between the target and the $i_{l,j}$th STA MLD, $j=1,2,3$. Since target position $(x,y)$ is unknown to the AP MLD, we replace $(x,y)$ in (9) with predicted target position $(\hat{x},\hat{y})$ in (4) and obtain the predicted CRLB of trilateration estimate as

$$\hat{C}_{t_{\mathcal{I}_l,l}} = \mathrm{Tr}\{\hat{\mathbf{\Psi}}_{\mathcal{I}_l,l}^{-1}\} = \mathrm{Tr}\{(\hat{\mathbf{\Gamma}}_{\mathcal{I}_l,l}\mathbf{D}_{\mathcal{I}_l,l}\hat{\mathbf{\Gamma}}_{\mathcal{I}_l,l}^T)^{-1}\}, \tag{10}$$

where $\hat{\mathbf{\Gamma}}_{\mathcal{I}_l,l} = \mathbf{\Gamma}_{\mathcal{I}_l,l}|_{(x,y)\leftarrow(\hat{x},\hat{y})}$. As $\hat{\mathbf{\Gamma}}_{\mathcal{I}_l,l}$ is a full rank matrix and $\mathbf{D}_{\mathcal{I}_l,l}$ is a diagonal matrix whose diagonal entries are all positive, $\hat{\mathbf{\Psi}}_{\mathcal{I}_l,l}$ is a symmetric positive definite matrix.

In consequence, the AP MLD achieves the best trilateration performance in UL sensing by selecting three STA MLDs of indices $\mathcal{I}_l \in [\mathcal{I}_l^a]^3$ with minimum predicted CRLB of trilateration estimate $\hat{C}_{t_{\mathcal{I}_l,l}} = \mathrm{Tr}\{\hat{\mathbf{\Psi}}_{\mathcal{I}_l,l}^{-1}\}$ in (10), which is equivalent to solving the optimization problem (11) below:

$$\min_{\hat{\mathbf{\Psi}}\in\mathbf{S}_{++}^2} \quad \mathrm{Tr}\{\hat{\mathbf{\Psi}}^{-1}\} \tag{11a}$$

$$\text{subject to} \quad \hat{\mathbf{\Psi}} \in \{\hat{\mathbf{\Psi}}_{\mathcal{I}_l,l} : \mathcal{I}_l \in [\mathcal{I}_l^a]^3\} \tag{11b}$$

The objective function (11a) is convex in $\hat{\mathbf{\Psi}}$ (the trace function of the inverse of a symmetric positive definite matrix is convex), and the constraint (11b) specifies the set of choices for $\hat{\mathbf{\Psi}}$. Hence, the optimization problem (11) is a discrete convex optimization problem and can be solved efficiently with existing practical techniques (e.g., [16], [17]).

### C. STA MLD Selection for DL Communications

When the AP MLD intends to conduct communications ($\beta = 0$), it needs to select some STA MLDs of indices $\mathcal{I}_l \subseteq \mathcal{I}_l^a$ for DL communications. Considering both throughput and fairness, the AP MLD aims to achieve weighted proportional fairness [13], which is equivalent to solving the optimization problem (12) below:

$$\max_{\mathcal{I}_l\subseteq\mathcal{I}_l^a} \quad \sum_{m\in\mathcal{I}_l} w_m \log(b_m^x) \tag{12a}$$

$$\text{subject to} \quad \sum_{m\in\mathcal{I}_l} b_m^x \leq p_l \tag{12b}$$

The objective function (12a) is the sum of weighted utility, where $w_m$ is the weight assigned to the $m$th STA MLD, and the constraint (12b) specifies the upper bound $p_l$ of number of bytes to be transmitted DL through the $l$th channel. Note that the optimization problem (12) is an NP-hard knapsack problem [12]. Hence, we develop an efficient fairness-aware STA MLD selection heuristic approach, as illustrated in Algorithm 2.

**Algorithm 2:** Fairness-Aware STA MLD Selection

**Input:** $\{(b_m^r, b_m^x)\}_{m\in\mathcal{I}_l^a}$
**Initialization:** $\mathcal{I}_l = \varnothing, p_l' = p_l$
**z-score normalization:** $\{b_m^r\}_{m\in\mathcal{I}_l^a} \rightarrow \{z_{s_m}\}_{m\in\mathcal{I}_l^a}$
**for** $m \in \mathcal{I}_l^a$
  $w_m = \exp(-z_{s_m})$; $\psi_m = w_m\log(b_m^x)/b_m^x$
**end for**
**Sort:** $\psi_{j_1} \geq \psi_{j_2} \geq ... \geq \psi_{j_{|\mathcal{I}_l^a|}}, j_1, j_2, ..., j_{|\mathcal{I}_l^a|} \in \mathcal{I}_l^a$
**for** $k = 1 : |\mathcal{I}_l^a|$
  $\mathcal{I}_l \leftarrow \mathcal{I}_l \cup j_k$; $p_l' \leftarrow p_l' - b_{j_k}^x$
  **if** $p_l' < 0$
    **break**
  **end if**
**end for**
**Output:** $\mathcal{I}_l$

Denote the remaining number of bytes that can be transmitted DL through the $l$th channel as $p_l'$. Then, we initialize $\mathcal{I}_l = \varnothing$ and $p_l' = p_l$, and normalize the number of bytes that have been received DL $\{b_m^r\}_{m\in\mathcal{I}_l^a}$ into z-score $\{z_{s_m}\}_{m\in\mathcal{I}_l^a}$. When the $m$th STA MLD suffers from a lower z-score $z_{s_m}$ (i.e., fewer bytes received DL), it should be assigned a larger weight $w_m$. Thus, we assign the weight $w_m = \exp(-z_{s_m})$ to the $m$th STA MLD. To maximize the sum of weighted utility in (12a), an STA MLD with a larger average weighted utility per byte is greedily given higher priority, where the average weighted utility per byte of the $m$th STA MLD is

$$\psi_m = w_m\log(b_m^x)/b_m^x. \tag{13}$$

Accordingly, an order of indices of STA MLDs to be addressed is created as $j_1, j_2, ..., j_{|\mathcal{I}_l^a|} \in \mathcal{I}_l^a$ with $\psi_{j_1} \geq \psi_{j_2} \geq ... \geq \psi_{j_{|\mathcal{I}_l^a|}}$ sorted in descending order. For the $j_k$th STA MLD, $k = 1, 2, ..., |\mathcal{I}_l^a|$, the index $j_k$ is added to $\mathcal{I}_l$ and the number of its bytes to be transmitted DL $b_{j_k}^x$ is subtracted from the remaining number of bytes that can be transmitted DL through the $l$th channel $p_l'$. Once $p_l'$ goes below zero, the STA MLD selection ends with the resulting $\mathcal{I}_l$.

## IV. Simulation

In this section, we evaluate the performance of *WiHound*. Specifically, we compare *WiHound* with three baseline methods on their sensing and communications performance, and examine the effect of number of STA MLDs on the sensing performance of *WiHound*. The evaluations are simulated with a Wi-Fi network featuring both EMLSR operation and ISAC functionality in MATLAB.

Below are three baseline methods (reduced from *WiHound*):

- **Random decision between sensing and communications (RDSC)**: The value of binary variable $\beta$ is randomly chosen from $\{0, 1\}$.
- **Random STA MLD selection (RSMS)**: The STA MLD index set $\mathcal{I}_l$ is randomly selected from $[\mathcal{I}_l^a]^3$ for UL sensing or randomly selected as a subset of $\mathcal{I}_l^a$ (under byte upper bound $p_l$) for DL communications.
- **Single link (SL)**: The number of interfaces $L$ is 1.

### A. Parameter Settings

On a 2D area, the Wi-Fi network comprises an AP MLD and $M$ STA MLDs which are randomly located with x and y coordinates uniformly chosen from $[-10, 10]$ m and a moving target with initial position at origin $(0, 0)$ and initial velocity of 1 m/s in a random direction. Each MLD has $L = 3$ interfaces of carrier frequency 2.437, 5.250, and 6.295 GHz with respective channels of channel bandwidth 40, 80, and 160 MHz. The SL method uses a single interface of carrier frequency 2.437 GHz with a channel of channel bandwidth 40 MHz. The byte upper bound $\{p_l\}_{l=1}^L$ is computed with the Shannon-Hartley theorem [18]. For brevity, we summarize key Wi-Fi network parameter settings in Table I.

TABLE I
Wi-Fi Network Parameter Settings

| Parameter | Value |
|---|---|
| AP MLD and STA MLD position | Random |
| Target initial position | $(0, 0)$ |
| Target initial velocity | 1 m/s in random direction |
| # interface $L$ | 3 |
| Carrier frequency | 2.437, 5.250, 6.295 GHz |
| Channel bandwidth | 40, 80, 160 MHz |
| Time window duration $\tau_w$ | 10.24 ms |
| # time window | 100 |
| DL data rate for an STA MLD | 20 Mbps |
| $(\tau_{SIFS}, \tau_{TF}, \tau_{CTS}/\tau_{ACK}, \tau_{NDP})$ | (16, 10.8, 4.6, 44+8$\rho\eta$) $\mu$s |
| # EHT-LTF symbol $\rho$ | 4 |
| # EHT-LTF repetition $\eta$ | 4 |
| Process noise intensity $g_s$ | 0.1 |
| Channel model | IEEE 802.11be indoor |
| AP MLD interface Tx power | 43 dBm |
| STA MLD interface Tx power | 23 dBm |
| Multiple-input multiple-output (MIMO) | $4 \times 2$ |

In the simulation, we execute three evaluations over $\alpha = \{0.025, 0.05, 0.1, 0.2, 0.5, 0.8\}$, with sensing performance quantified in terms of MSE between target position $(x, y)$ and predicted target position $(\hat{x}, \hat{y})$ and communications performance quantified in terms of throughput and Jain's fairness index [19]. The first evaluation assesses the sensing performance with number of STA MLDs $M = 8$. Next, the second evaluation assesses the communications performance with number of STA MLDs $M = 8$. Lastly, the third evaluation inspects how number of STA MLDs $M$ affects the sensing performance of *WiHound* across $M = \{4, 8, 12\}$.

### B. Evaluation Results

The results of the first evaluation (sensing performance) are shown in Fig. 3, which demonstrates the MSE between target position $(x, y)$ and predicted target position $(\hat{x}, \hat{y})$ under the four methods (*WiHound*, RDSC, RSMS, and SL) with number of STA MLDs $M = 8$. Note that the MSE of the RDSC method is a constant over $\alpha$ since it randomly decides between sensing and communications, irrelevant to $\alpha$. On the contrary, the MSE of *WiHound*, RSMS, and SL methods decreases as $\alpha$ increases (with more favor on sensing). It can be observed that *WiHound* always outperforms the RSMS and SL methods in terms of MSE. This is because *WiHound* selects three STA MLDs of minimum predicted CRLB of trilateration estimate for sensing frequently across its $L$ interfaces, while the RSMS method suffers from a largely fluctuating trilateration performance (with random STA MLD selection) and the SL method suffers from less frequent sensing (with its single interface). In contrast to the RDSC method of a fixed sensing performance, *WiHound* can take advantage of the flexible configuration of $\alpha$ to satisfy different sensing performance requirements.

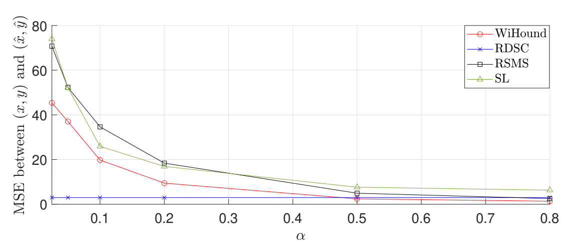
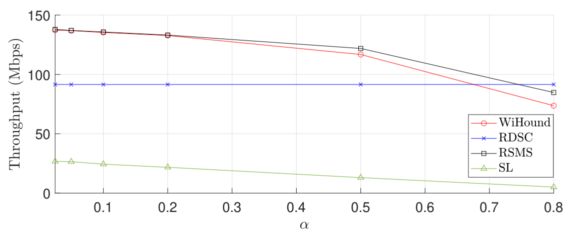


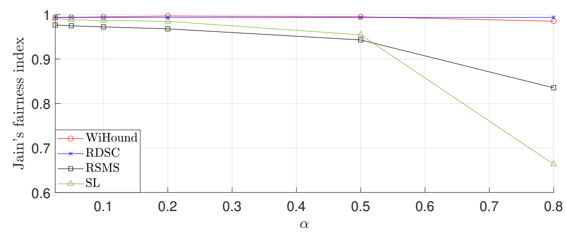

Fig. 3. MSE between target position $(x, y)$ and predicted target position $(\hat{x}, \hat{y})$ under different methods with number of STA MLDs $M = 8$

For the second evaluation (communications performance), its results are shown in Fig. 4, where Figs. 4(a) and 4(b) demonstrate the throughput and Jain's fairness index, respectively, under the four methods (*WiHound*, RDSC, RSMS, and SL) with number of STA MLDs $M = 8$. Similarly, the RDSC method is limited by its fixed communications performance. Both the throughput and Jain's fairness index of *WiHound*, RSMS, and SL methods decrease as $\alpha$ increases (with less favor on communications). It can be found that *WiHound* always outperforms the SL method, which manifests the advantages of leveraging the synergy of multiple interfaces.

Compared to the RSMS method, *WiHound* achieves a stably high Jain's fairness index with great robustness over $\alpha$, thanks to its fairness-aware STA MLD selection, with only a slight degradation of throughput. This reveals the ability of *WiHound* to ensure a high fairness while maintaining a high throughput.




(a) Throughput




(b) Jain's fairness index

Fig. 4. Throughput and Jain's fairness index under different methods with number of STA MLDs $M = 8$

Fig. 5 shows the results of the third evaluation (effect of number of STA MLDs $M$ on sensing performance), demonstrating the MSE between target position $(x, y)$ and predicted target position $(\hat{x}, \hat{y})$ of *WiHound* across $M = \{4, 8, 12\}$. Decreasing as $\alpha$ increases (similarly), the MSE of *WiHound* decreases as $M$ increases as well, since it is more possible to select three STA MLDs of smaller predicted CRLB of trilateration estimate from more STA MLD candidates.

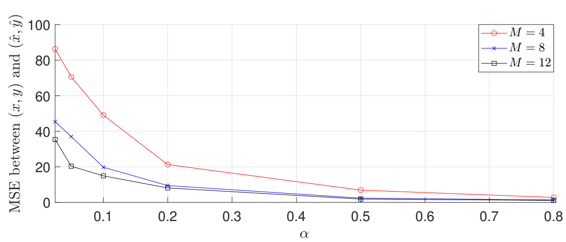



Fig. 5. MSE between target position $(x, y)$ and predicted target position $(\hat{x}, \hat{y})$ of *WiHound* under different numbers of STA MLDs $M = \{4, 8, 12\}$

## V. Conclusion

In this paper, we propose *WiHound*, a novel method for target tracking with ISAC using EMLSR in IEEE 802.11 WLANs, supported by next-generation IEEE 802.11be and IEEE 802.11bf amendments. Particularly, the target is tracked by the Kalman filter with trilateration measurements, and a score-based ISAC decision approach is developed for the AP MLD to decide between sensing and communications at every TXOP under EMLSR. For a sensing TXOP, three STA MLDs required in trilateration are selected by solving a CRLB-based discrete convex optimization problem. Conversely, for a communications TXOP, an efficient fairness-aware STA MLD selection heuristic approach is developed for a unique knapsack problem with respect to weighted proportional fairness. Simulation results verify that *WiHound* strikes a good balance between sensing and communications performance. Besides, an increase in number of STA MLDs improves the sensing performance of *WiHound*.


## Acknowledgment

This work was supported in part by the Wayne J. Holman Chair and the EVP for Research at Georgia Tech.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