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KRAFT: Kalman Filter based Energy-aware LTE and Wi-Fi Joint Throughput Optimization

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Abstract--- Resource block allocation in LTE is a complex metric consisting of available bandwidth, required data rate and channel state conditions. A Wi-Fi access point, co-operating with LTE eNB can service a single User Equipment (UE) through multiple interfaces (multihoming) for improving throughput. The challenge is to inter-operate the greedy LTE scheduler with deferral-based Wi-Fi band allocation. A joint scheduling therefore is a complex problem requiring a robust estimation method which not only optimize per-user throughput but also can support a minimum average system throughput condition. Kalman filter provides resource prediction while minimizing the mean square error. In this paper, we propose KRAFT, a novel LTE and Wi-Fi joint scheduler using Kalman filter. We periodically measure the discrete SINR values, available bandwidth and resource requirements to predict the system throughput optimized scheduling among Wi-Fi and LTE networks. Also, an energy-aware scheduling algorithm is proposed as a tie breaker between all the other approaches.

Keywords--- Kalman Filter, Wi-Fi, LTE, Throughput Optimization.

I. INTRODUCTION

Last decade has seen enormous growth in the number of total mobile devices which are currently more than a Billion in number across the world as per [1, 18]. A mobile device along with multiple sensors such as camera, accelerometer, gyroscope etc., has capabilities to connect to other devices using more than one interface such as Bluetooth [2], Wi-Fi, General Packet Radio Service (GPRS) [3], Universal Mobile Telecommunications System (UMTS), Long Term Evolution (LTE) and so on. More recently, mm Wave [4] and 5G-New Radio (5G-NR) predictions are surrounding with their corresponding technologies in terms of interfaces to provide these accesses.

As the number of sensors and interfaces increase in a mobile device, on one hand its overall throughput increases due to better technology, while on the other hand, its energy consumption rises because of increase in computing instructions per second. Therefore, a newer interface in a mobile device is required to have tradeoff between the total throughput and energy consumed.

With the advent of these multiple interfaces, it has become necessary to design solutions which can use all of them simultaneously without hampering the battery performance. It is shown that concurrent multipath transmissions [5], [6], [7], [8] can improve the overall throughput performance of a device which require either a router splitting the traffic flow or device initiating multiple TCP connections. In either case, a coordination among the role of available access technologies is critical in resource allocation and management.

Utilizing multiple interfaces of a device is challenging because of multiple reasons such as: (i) lack of interface coordination, (ii) lack of aggregation statistics, (iii) unreliable load sharing and balancing, (iv) improper scheduling, and (v) inter-symbol as well as inter-radio interferences.

The challenges, (i)-(ii) can be solved using an on-device scheduler with aggregator which should not only be able to expose the current status of the interfaces from the Kernel to the application but also should be able to coordinate usage of these interfaces. The load sharing problem i.e. challenge (iii), is therefore an extension of scheduling problem wherein a rate distributed to interfaces according to the network dynamism and application requirements can be assumed to satisfy the load balancing inherently. Finally, the challenge (iv) and (v) need to be solved from the network side and require much deeper analysis to solve challenges arising from factors such as multi-path propagation, user mobility etc. and therefore, need more careful considerations.

Multihoming is a technique to use multiple interfaces simultaneously to optimize application throughput. Attempts are made in [9] to address multihoming issues by using a host-based identity protocol where a name-based networking schema is used to expose the transport layer issues to the network layer and later performing a joint optimization. Platform to support multihoming is proposed and described in [10]. The paper elaborates that in order to support multiple interfaces, each of them should be optimized for their quality performance. A joint resource allocation-based scheme is designed in [11] considering heterogeneous networks and two types of users: single networked, and multihomed. The problem is formulated as a convex problem and results are shown to improve system capacity.

A multihoming scenario is described in the Figure 1 where a User Equipment (UE) can in the common range of Access Point 1 (AP1) and Access Point 2 (AP2). The left figure shows that AP2 is completely shadowed by AP1 and AP2s users will be subset of AP1s users.

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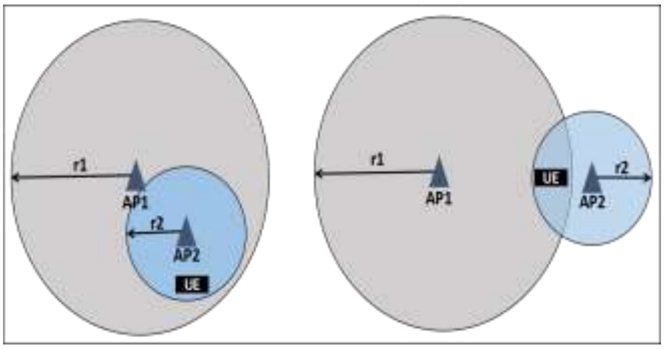

Fig. 1: Coexistent Network Scenarios: Complete Overlap (left) and Intersecting region (right)

The right-side figure highlights that AP2 can serve additional users apart from serving common users with AP1. Traditionally, numbers of users served by AP1 and AP2 are disjoint and therefore total number of users are more. For the scenarios shown in Fig. 1, for a single user, multiple APs can provide service and therefore there is a throughput optimization avenue available for that user.

The approaches covered in literature are disjoint to the fact that challenges (i)-(v) are to be satisfied by a single system for a goal of overall optimization. The network interfaces use their corresponding frequency bands to send and receive data from a UE. In order to serve the overall users in a coherent and throughput-satisfying way, a joint estimate of throughput from multiple interfaces is essential. Kalman filter provides a way to estimate resources using a linear quadratic estimation method. In a very first usage of this property to the best of our knowledge, this paper builds upon an overall system to optimize throughput using Kalman filter for the joint optimization of throughput in a multi-homed scenario.

The system is compared between distributed as well as centralized optimization and a tie- breaker using energy is proposed.

The rest of the paper is organized as follows. Section 2 explains the mutlihoming scenario in detail with an emphasis on our approach to deal with a heterogeneous system. Section 3 provides details of Kalman filter with respect to the proposed system scenario. A distributed approach is compared with a centralized approach in Section 4. Section 5 presents numerical analysis and results while the conclusions are drawn in Section 6 with an overview about our future work.

II. THE PARADIGM OF MULTIHOMING

The Internet has evolved as a network of multiple heterogeneous networks with varied hardware, software, frequency spectrum and access devices. Figure 2 illustrates one such heterogeneous system in which a UE receives signals from an eNB and a 5G Femtocell.

The smartphones can scan more than 20 neighboring base-stations simultaneously before selecting a single largest signal strength as a home carrier.

Using the gigahertz level processing capabilities of a UE moving towards faster clock cycles augmented with next generation of scheduling algorithms, it is possible to use multiple radios simultaneously.

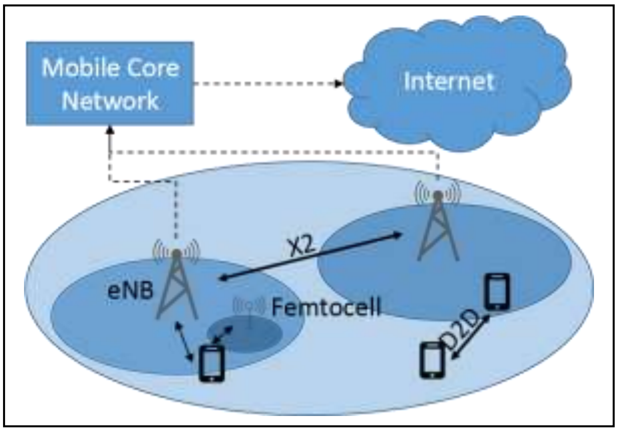

Fig.2: Network Multihoming Illustration

A. *System Considerations*

The multihoming scenario has various participating entities in the system. At the bottommost layer, there are resource- hungry devices which contend or share throughput, at the middle layer, the resources are allocated to the devices and at the topmost layer, the decision for resource allocation is typically made. Understanding these system considerations is important to design a robust and scalable scheduler and are presented here.

D2D Communication

The device to device (D2D) communication is widely stud- ied [12], [13] for collaborative or shared network usage. A mobile hotspot is an example in which a dongle or mobile device serves other devices in the vicinity using the Wi-Fi technology while the backhaul is also wireless, primarily LTE network in the MHz spectrum range.

X2-based Signaling

Implications arising from user mobility such as change in signal strengh and handover are communicated among eNBs (evolved node-B) using X2 signaling interface [14]. In case of vertical radio technologies, a signaling compatibility or fallback mechanism is considered for smooth information exchange between the network points.

Multi-Radio

Different technologies bring multiple inter-operability challenges. For example: LTE eNBs operate in the ~MHz range while the LTE Femtocell and 801.11 based Wi-Fi operate in the ~2.4 GHz range. Moreover, the packet scheduling and contention mechanisms in all these technologies is also different. Therefore, when designing a joint scheduler considering these technologies, the heterogeneity of the parameters should be considered fully.

Decision Mechanism

The joint scheduling problem can be dealt either centrally [15] at the mobile core network or in a distributed fashion at the traffic entry points by self-coordination mechanisms. In both these methods, there is a difference in the energy consumptions due to control plane message exchanges and energy savings by optimizing the network usage itself.

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B. System Design

For a heterogeneous system shown in Figure 2, the specific design choices such as signal fading, user throughput, sys- tem throughput, and packet loss are to be considered. Here, we describe ways of approaching the problem of resource scheduling for joint optimal throughput using Wi-Fi and LTE.

Channel Effects

Channel properties in a wireless communication system vary widely. A transmitted signal undergoes fading, mul- tipath and Doppler effect before reaching the destination. Moreover, there are added noise and interference which affect the signal quality.

Analyzing the impact of these parameters is necessary to build a throughput-optimized system. The signal variations in an Additive White Gaussian Noise (AWGN) channel due to Rayleigh fading are shown in Figure 3 by considering different Doppler frequencies. Multiple NLOS (non-line of sight) between the transmitter and the receiver causes the Rayleigh fading which assumes numerous reflection waves with i.i.d. (independent and identically distributed) property. Therefore, in case of multi-homing scenario, we consider channel effects on different waves directed towards a single receiver from multiple transmitters.

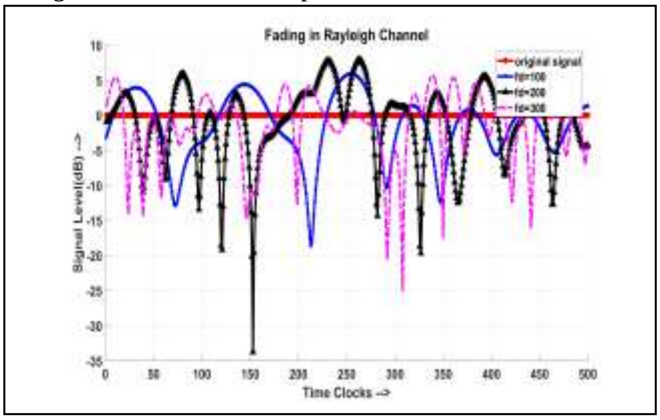

Fig. 3: Signal Variations with the Doppler Frequency

Channel Estimation

The channel knowledge in an LTE system is acquired by sending periodic pilot signals (already known at the re- ceiver) before sending the data. This assists eNB in synchronization, timings, transmission rate, coding and modulation scheme, and finding channel state information. The channel conditions are estimated and tracked continuously using the feedback given by the receiver. Due to large scale and small scale fading, the channel state varies in about every 5 ms. Due to this variations, there are channel estimation errors which further leads to signal detection. Therefore, a robust channel estimator is required for a optimal system design.

C. A Case for the Kalman Filter

As discussed earlier, designing a multi-homing system re- quires a robust channel estimator which can adopt itself timely and can incorporate multiple system parameters inherently. Kalman filtering which uses the linear quadratic estimation on a series of observations over time to produce a close estimate within an interval. This is a critical step in multi-homing given the fact that channel effects and estimation errors adversely affect the system throughput. Therefore, in the next section, we describe a Kalman filter based LTE and Wi-Fi joint scheduler with an objective to optimize the system throughput.

III. KALMAN FILTER BASED LTE AND WIFI SCHEDULER

Resource scheduling in a multi-homing system requires inputs and estimations from various entities.

In general, the joint scheduling of LTE and Wi-Fi can be done either by a cooperating control plane exchange between two Access Points (APs) in the resource plane or using a central con- troller with a global view of the network as illustrated in the Figure 4.

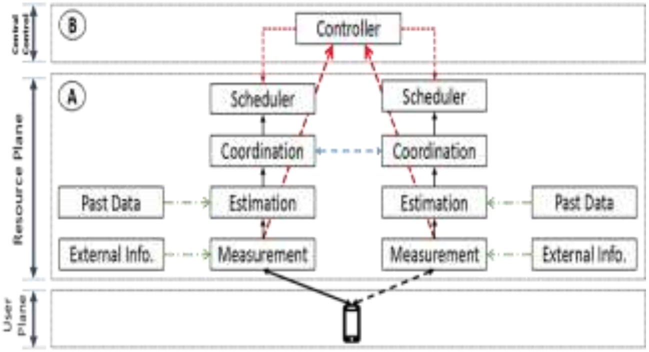

Fig.4: Illustration of Resource Scheduling using Estimation

The user plane provides information to the resource plane consisting of APs. The part (A) in the figure highlights the distributed control plane while the (B) part shows a global decision method. In a hybrid system, A and B can be combined.

The resource plane gathers measurements from the UE, external data such as other UEs signal strength, resource block (RBs) allocations, and past stored data such as signal to noise ratio, to estimate the channel conditions. These estimations in a distributed control are communicated to the other AP whose scheduler decides based upon a joint metric which resource is to be allocated to a given UE. For the central scheme, the controller estimates and schedules jointly using global state information available. The rest of this section describes how we build independent modules described in the Figure 4.

UE State Estimation

Kalman filter can be used to estimate the channel state conditions as shown in [16] and later adjusting throughput using the scheduling algorithms [17].

In this work, we combine channel state information and the joint scheduling algorithm to determine the UE state. The channel state is estimated using Kalman filter approach as shown in the Figure 5.

Kalman Estimator

At each of the Kalman Estimator (KE), the inputs such as Signal to Noise Interference Ratio (SINR), Bit Error Rate (BER), Throughput (Current) and Policy information such as proportional fair or maximum throughput is correlated with the previous state information to estimate the next state.

Joint Scheduler

The Joint Scheduler (JE) takes input from the Kalman Estimator for LTE as well as Wi-Fi. In a distributed scenario (Part A in the Figure 4), the JE is

placed at each of the APs or eNBs. For a central controller case (Part B in the Figure 4), the JE is placed at the central node which optimizes system globally at the cost of collected control plane which introduces additional latency into the resource allocation decision process. This is an iterative process where the inputs to the JE are used to finalize the allocated resources to each of the UEs in the system.

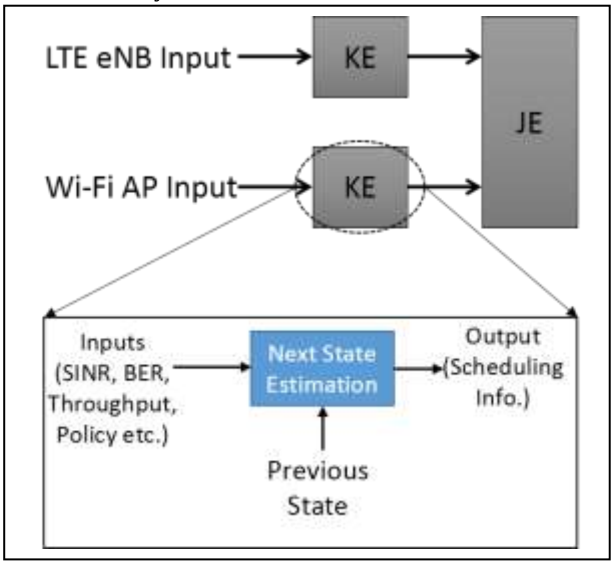

Fig. 5: Channel State Estimation and Joint Scheduling

The next section describes our system model to achieve the joint throughput optimization.

IV. SYSTEM MODEL

Consider a receiver (UE) receiving inputs from multiple transmitters (Wi-Fi AP and LTE eNB) through an AWGN channel. The estimated output at the UE, *k*, from any one of the transmitter can be given as:

$$\tilde{y}_k(t) = x_k(t) + n(t) \qquad (1)$$

In Equation 1, $x_k(t)$ is the transmitted signal and $n(t)$ is the channel noise at any given time t. Consider that a known pilot signal, $p(t)$ is sent from the transmitter to the UE, the signal error at the UE can be calculated as:

$$e_k(t) = p_k(t) - \tilde{p}_k(t) \qquad (2)$$

In Equation 2, $\tilde{p}_k(t)$ is the received pilot signal. The error or the received pilot signal should be sent back to the transmitter which should estimate signal to noise ratio and bit error rate for the UE.

The system itself introduces some errors along with the external errors due to problems in the estimation, transmit-ter and receiver hardware, and channel noise. These additional errors are propagated while measuring the system parameters. The measured parameters are called observed state from which, using proper techniques, one can estimate the optimal system state. For linear systems with AWGN properties which introduce Gaussian errors, Kalman filter can recursively provide best estimate from the available observed states. Further, for non-linear system, one can qualify the system optimally which is out of scope in this work. Next, we describe the Kalman specific parameters, a joint throughput estimator and finally, providing energy optimization by proposing KRAFT which considers the accuracy of estimates and energy consumption before deciding on the scheduling.

Kalman Estimator for Single Paramter

The Kalman estimator presented here has three phases: estimation, prediction and correction. For a random variable, *X*, the expected value over time, *T* is given by:

$$E_T[x] = \int_0^T x * p(x)dx = \bar{x} \qquad (3)$$

In Equation 3, p(x) is the weight given to a value x. Considering 'T' to be periodic and in the order of ∼ms for an LTE RB scheduling case, we can also find the discrete average of Equation 3 as:

$$\tilde{x} = \frac{1}{N}\sum_{j=1}^{N} x_j \qquad (4)$$

On the similar thoughts, the variance σ^2 and co-variance of i^{th} sample with respect to the j^{th}, Cij can be defined in the discrete format. Therefore, the co-variance matrix, C for an i.i.d process, one parameter can be defined as:

$$C = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{m1} & \cdots & C_{mn} \end{bmatrix} \qquad (5)$$

Therefore, the current state of a random variable *X* can be found out using the previous states as follows for a linear estimation:

$$x_k = \Phi_{k-1} x_{k-1} + N \quad (6)$$

In Equation 6, N is the random variable of Gaussian noise drawn from $N(0, C)$ and Φ_{k-1} is the state transition matrix at $k - 1$. In the prediction stage, a new state is calculated from the previous state incorporating old estimates using:

$$x_k' = \phi_{k-1}\bar{x}_{k-1} \qquad (7)$$

Observe that in Equation 7, there might be additional error introduced due to estimation from an estimate. This is corrected in the third stage, correction as follows:

$$\bar{x}_k = x_k' + (G * E) \qquad (8)$$

In Equation 8, *G* is the gain of Kalman filter and *E* is the error in the previous estimates. This recursive approach can estimate the state of a single parameter in the system. Next, we will build model to combine multiple parameters.

Joint Estimation

For a set of parameters, a joint estimation can provide us a way to provide better estimates of input variables and hence the throughput decisions can be improved. The joint estimation is similar to finding a correlated instance of random variables.

The co-variance of two random variables $X1$ and $X2$ is given by:

$$Cov\,(X1, X2) = E\,[(X1\; - \;E[\,X1\,])(X2\; - \;E[\,X2\,])] \qquad (9)$$

If the expression presented in Equation 9 is positive on taking an average, it can be simplified as:

$$Cvar\; = E\,[X1X2] - E[\,X1]E[X2] \qquad (10)$$

For a system with two parameters, a joint estimation then can be carried out by inputting $Cvar$ in the Eq. 8 as follows:

$$\bar{C}_{var} = C'_{var} + (G * E) \qquad (11)$$

Finally, as $\bar{C}_{var}$ in the Equation 11 evolves as a multivariate random walk, the positivity of one variable affects the lag of other and vice-versa. This property captures both the variables simultaneously in making the decision. Next sub- section illustrates using KRAFT for energy aware decisions for throughput optimization.

Energy Aware Decisions with KRAFT

In this subsection, we explain how a joint estimation using the Kalman filter enhances the performance of a system in an energy-aware scenario. We call this model, KRAFT. In KRAFT, along with one user-specific parameter, there is always an energy parameters associated while modeling using Equation 10.

In an unbiased Kalman filter, the estimation of one parameter impacts that of other as the parameters are not i.i.d (independent and identically distributed) which results in the change of Kalman gain by fluctuating numerical values. When discretized, these parameters carry their states to the next estimate and therefore provide a general mechanism to satisfy our requirement of finding the future value.

KRAFT assigns each of the input parameters to the system as shown in Figure 5. The energy is always assigned the highest weight and therefore the system is favorable towards saving energy. For each set of parameters, the throughput is then estimated using the optimized method described in [17, 19, 20]. Finally, the throughput is estimated using four different scenarios as described in the following cases. In this work, following cases are analyzed.

1. *Case 1: Wi-Fi:*

Here, the decisions are solely based on the Wi-Fi and LTE is not taken into the considerations.

2. *Case 2: LTE:*

Like above, here only LTE is taken into consideration for scheduling.

3. *Case 3: Joint:*

In this case, both LTE and Wi-Fi are jointly scheduled as illustrated in the earlier subsection.

4. *Case 4: KRAFT:*

Here, KRAFT is simulated to provide energy the prime importance while scheduling.

Next section discusses the results obtained in this work.

V. RESULTS

The prime objective of this work is to provide a mechanism for joint scheduling while saving energy.

Figure 6 shows the energy usage between multiple approaches on a normalized scale. For small number of users (N=50), both Joint and Kraft are able to serve better. The reason is Joint works by allocating Wi-Fi and LTE resources in the order of preference and availability which for small set of users can be satisfied without large scale estimations, and therefore is similar to KRAFT.

In case of small number of users, the energy consumed by Wi-Fi only and LTE-only is almost half as compared to the other two approaches which is due to the fact that individual approaches do not focus on improving throughput but only on providing connectivity. As the number of users quadrupled (N=200), KRAFT per- forms at least 20% better than Joint by considering energy optimization. The LTE-only approach while in this case becomes power hungry because of the fact that LTE can provide more data rate to the users at the cost of using more energy.

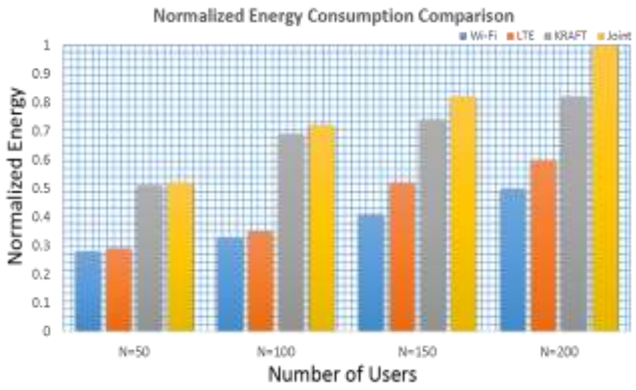

Fig. 6: Comparing Energy Usage between Multiple Approaches

Figure 7 compares the throughput (in Mbps) of various approaches for the parameters similar to [7]. The throughput of Wi-Fi is based upon CSMA/CA approach which depends upon contention. Therefore as the number of resource block to be allocated increase, the throughput goes down and is minimum of all the approaches. For LTE, the throughput is based upon centrally allocated resource block scheduling mechanism which outperforms Wi-Fi only system. In case of Joint, the throughput is a factor of coordinated assignment and therefore for small RBs it is more than the KRAFT in some cases while KRAFT, as it considers the overall metrics in order to evaluate the assignment by estimation outperforms almost all the schemes.

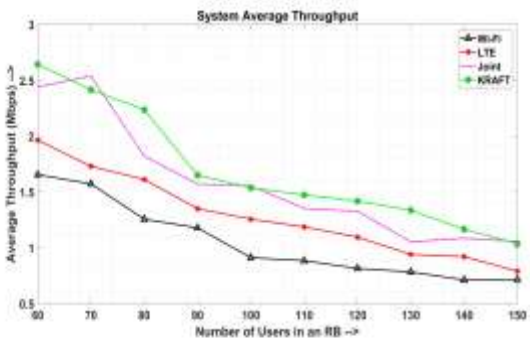

Fig.7: Comparing Throughput of Multiple Schemes

VI. CONCLUSION

In this work, a Kalman filter based energy-aware joint estimator for resource block scheduling in LTE and Wi-Fi is designed. We call it KRAFT. A cooperative system in which Wi-Fi access point (AP) works in accord with the LTE eNB is proposed which can support a User Equipment's (UE) Quality of Experience (QoE) needs by allowing it to connect through multiple interfaces. The challenge of interoperability between the greedy LTE scheduler and the deferral based Wi-Fi band allocation is solved by providing an exchange mechanism. The discrete SINR values, available bandwidth and resource requirements are periodically measured to estimate the system throughput optimized scheduling among Wi-Fi and LTE networks. Finally, an energy-aware scheduling algorithm is proposed as a tie breaker between all the other approaches such as Wi-Fi only, LTE only and Joint. It is shown that KRAFT outperforms all other approaches both in terms of energy savings and throughput. Out future work includes emulating the proposed framework on a real-time testbed.

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