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Slotted Aloha-NOMA with MIMO Beamforming for Massive M2M Communication in IoT Networks

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***Abstract*—This paper proposes an uncoordinated random medium access protocol for Internet of Thing (IoT) networks incorporating conventional slotted Aloha (SA) with power domain non-orthogonal multiple access (PD-NOMA) and multiple-input multiple-output beamforming (MIMO BF). The number of active IoT devices, which is not known *a priori*, is detected at the IoT gateway via multiple hypothesis testing. The proposed protocol referred to as BF-SA-NOMA is not only scalable and compatible with the power-limited IoT devices, but it also uses beamforming to significantly improve the throughput to 1.31 compared with 0.36 in conventional slotted Aloha when 6 active IoT devices can be successfully separated using 2×2 MIMO and a SIC (Successive Interference Cancellation) receiver with 3 optimum power levels. The simulation results further show that the proposed protocol achieves higher throughput than Aloha-NOMA with a lower average channel access delay.**

I. Introduction

The rapid growth of both the number of connected devices and the data volume that is expected to be associated with IoT applications, has increased the popularity of Machine-to-Machine (M2M) type communication within 5G wireless communication systems [1]. Hence, it is necessary to rethink the medium access control (MAC) protocol to match the massive amount of devices accessing the shared medium and the limited-power and low complexity requirements of IoT devices.

Coordinated medium access protocols such as time-division multiple access (TDMA), frequency-division multiple access (FDMA), or code-division multiple access (CDMA) are contention-free protocols via ensuring that resources are exclusively scheduled for each device. However, these protocols are not scalable and cannot provide sufficient throughput to meet the demands for a massive number of IoT devices due to the empty slots and the scheduling overhead required for the connection establishment before each transmission.

Therefore, uncoordinated random access protocols have attracted lots of attention in the standards as a possible method for making massive number of M2M communication of short packets possible with a low signaling overhead [2], [3]. On the other hand, uncoordinated medium access protocols such as Aloha and slotted Aloha (SA) perform well in small networks only, and cannot provide sufficient throughput in networks with large number of IoT devices transmitting all at once over the shared medium due to collisions at the IoT gateway.

The same issues exist in IEEE 802.11, which is based on carrier-sense multiple access with collision avoidance (CSMA/CA) where collisions can still happen due to the hidden and exposed terminal problems. Moreover, CSMA/CA is not compatible with the limited-power requirements of IoT devices since it requires continuous channel monitoring.

The proposed protocol exploits the simplicity of slotted Aloha (SA), the merit of MIMO beamforming in reducing collisions [4], and the superior throughput of non-orthogonal multiple access (NOMA) [5] and its ability to resolve collisions via use of successive interference cancellation (SIC) receiver [6], [7].

In [8], [9] the use of NOMA with Aloha was introduced as a random access protocol that can achieve a high throughput in comparison with conventional Aloha. Also, in [10] the throughput performance of NOMA with multiple sub-channels is studied by applying NOMA to another well-known random access scheme, multichannel Aloha [11]. Though, the MAC protocols in [8], [9] and [10] are promising candidates for IoT, they fall short achieving high throughput and a low channel-access delay for a large number of active IoT devices when the number of available radio resources is limited. Another drawback is high transmission power as the number of active IoT increases, which makes them incompatible with power-limited IoT devices.

The contributions of this paper can be summarized as follows. First, an uncoordinated random access protocol that is scalable, matched to the limited-power requirement of IoT devices, and has high throughput is proposed to be used in IoT networks. Secondly, a flexible frame structure for the proposed protocol is discussed. Following that, using a form of multiple hypotheses testing [12] at the IoT gateway to detect the number of active IoT devices (which is not known as *a priori* information) in order to adjust the SIC power levels is presented. Finally, simulation results are performed to show that the proposed protocol, BF-SA-NOMA, protocol, outperforms conventional slotted Aloha and Aloha-NOMA protocols in terms of throughput and channel access delay without excessively increasing the SIC power levels.

The paper is organized as follows. Section II discusses the proposed BF-SA-NOMA protocol, Section III presents a flexible frame structure for the proposed BF-SA-NOMA protocol. Section IV demonstrates the use of multiple hypotheses testing for detecting the number of active IoT devices. In Section V, simulation results are presented to show the superiority of the proposed method regarding throughput and channel

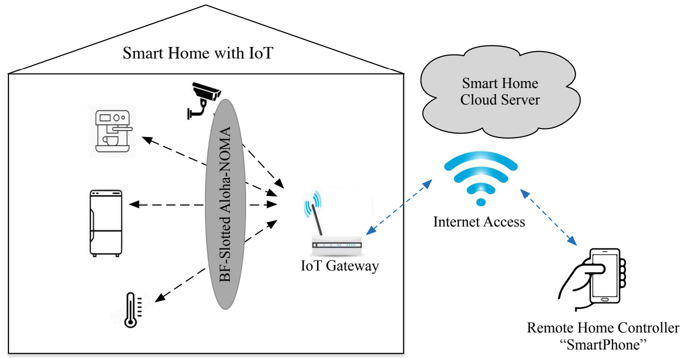

Fig. 1. A use case of BF-SA-NOMA in the smart home with IoT.

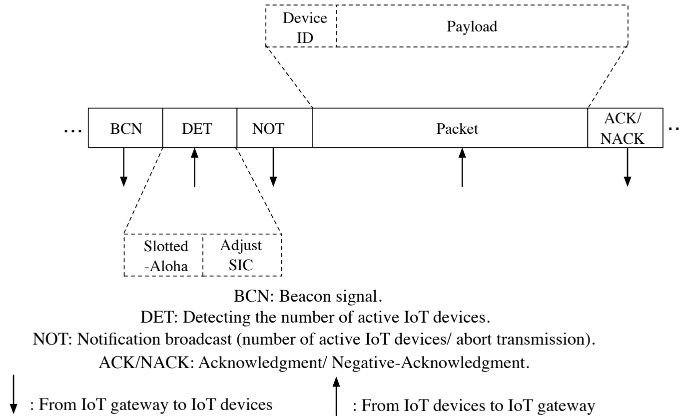

Fig. 2. The proposed protocol frame structure.

access delay with respect to the conventional slotted Aloha and Aloha-NOMA protocols. The paper is concluded with some remarks in Section VI.

II. BF-SA-NOMA Protocol in IoT Networks

The BF-SA-NOMA protocol is a synergistic combination of the low complexity SA protocol with the advantage of collision avoidance using MIMO-BF and the high throughput feature of NOMA. The main bottleneck of SA systems is the low throughput caused by the high number of collisions, which can be addressed by MIMO-BF and NOMA. In BF-SA-NOMA the signaling overhead is reduced in the detection phase of the proposed protocol where the number of active IoT devices are detected by the gateway using a form of multiple hypotheses testing, which is further explained in Section IV. It is also an energy efficient protocol due to the fact that MIMO-BF reduces collisions and SIC receiver resolves the residual collisions, and thus minimizes retransmission. Lastly, the proposed scheme increases the conventional SA throughput significantly. The BF-SA-NOMA protocol can be suitable for various scenarios where many IoT devices are transmitting simultaneously on the same frequency with different power levels to an IoT gateway and then the received signals can be separated via use of SIC receiver. A sample illustration of this scenario is depicted in Fig. 1 as a smart home with an IoT network. In this model, IoT devices send their data to the IoT gateway whenever they want using the BF-SA-NOMA protocol and the IoT gateway distinguish the signals with SIC receiver. Lastly, the proposed scheme increases the conventional SA throughput significantly.

III. Flexible Frame Structure

One of the main practical challenges for enabling the implementation of the BF-SA-NOMA protocol is the assignment of proper power levels for the IoT devices before transmitting the information; otherwise the signals received from different IoT devices cannot be extracted successively from the composite received signal. This issue becomes more challenging in dynamic environments where the number of IoT devices with information ready to send is continuously changing.

In this section, this challenge is addressed via a flexible frame structure. Such a scheme provides great flexibility in adapting to changing network environments. This structure is opposite to that of TDMA or FDMA in which a new user arrival can completely change the overall frame structure such the additional user must be assigned at least one slot within the frame.

As illustrated in Fig.2, the proposed frame structure is composed of 5 phases. In the first phase, the IoT gateway transmits a beacon signal to announce its readiness to receive packets. Next, the IoT devices with packets ready to transmit send a training sequence to aid the gateway in detecting the number of active IoT devices in the medium. The IoT gateway detects the number of devices requesting transmission via a form of multiple hypotheses testing, as further explained in Section IV, and adjusts the degree[1] of SIC receiver for the optimum power levels.

In practice, the SIC receiver has fixed range of optimum power levels (e.g. m=2,3). If the IoT devices are registered with the gateway instead of using multi-hypothesis testing, implementation would be simpler, however, this will significantly increase the length of the control phase and thus decrease the payload or throughput considering the potentially large number of IoT devices. In the third phase, if the detected number of active IoT devices is not in the range of the total optimal power levels the IoT gateway aborts the transmission and starts the frame again by sending a new beacon signal and implying that the active transmitters use a random backoff.

If the detected number of devices is in range of the SIC receiver, the IoT gateway broadcast the degree of SIC to the transmitters and then each active IoT device randomly picks one of receiving antennas using a pre-calculated precoding matrix, and also picks one of the optimum power levels. If the choices at each of the receiving antennas are distinct the SIC receiver can decode the self-identifying signals (device ID + payload) and then the gateway sends an ACK. However, if the active IoT devices did not select distinct power levels, the reselection process is repeated and after a few attempts if there is no successful transmission, the users receive a NACK and

[1]We denote a SIC receiver that can process m signals as SIC(m) and we refer to m as the SIC degree.

enter a random back-off mode. This improves fairness among the users and will allow for the possibility of fewer active users in the next session (which will improve the probability of successful transmission).

IV. Multiple Hypothesis Testing: Detecting The Number of Active IoT Devices

This section presents a form of multiple hypothesis testing to detect the number of active devices. The detection of active devices starts in the second phase of the BF-SA-NOMA frame as presented in Fig.2.

After receiving the beacon, all the IoT devices send at the same power level using slotted Aloha a training sequence (known to the IoT gateway) of length *L*. The superposed received signal at the IoT gateway from *N* active transmitting IoT devices is given by

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{w}, \tag{1}$$

where $\mathbf{H} = [h_1, , h_2, ..., h_N] \in \mathbb{R}^{1\times N}$, h_n is the channel gain between the n^{th} IoT device and the IoT gateway, $\mathbf{s} \in \mathbb{R}^{N\times L}$ is the transmit sequence (e.g. BPSK) from N IoT active devices and $\mathbf{w} \in \mathbb{R}^{1\times L}$ is the additive white Gaussian noise with zero mean and variance σ^2. The multiple hypothesis test is used to detect the number of N active IoT devices from the total M IoT devices. The following procedure is used to sequentially detect the number of active devices

$$\begin{aligned}
&\mathcal{H}_0 : \text{Received signal contains only noise}\\
&\quad \mathbf{y} = \mathbf{w},\\
&\mathcal{H}_1 : \text{Received signal contains}\\
&\quad \text{data from at least one IoT device}\\
&\quad \mathbf{y} = h_1 s_1 + \mathbf{w},\\
&\mathcal{H}_N : \text{Received signal contains}\\
&\quad \text{data from at most } N \text{ IoT device}\\
&\quad \mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{w}
\end{aligned} \tag{2}$$

We assume $h_n = 1$, $\forall n \in \{1, 2, ..., N\}$. Following the Neyman-Pearson (NP) test, we can write the Likelihood Ratio (LR) testing [12] $\mathcal{H}_N$ Vs. $\mathcal{H}_{(N-1)}$ as in (3), where $\mathbf{s}_n \in \mathbb{R}^{1\times L}$ is the transmitted sequence from n^{th} IoT device. By taking the logarithm, (3) is simplified to (4).

The NP detector or the test statistics in (4) compares the sample mean of the received signal to the threshold $\gamma\prime$ to decide on a hypothesis $\mathcal{H}_N$ or $\mathcal{H}_{N-1}$. The NP test terminates if the number of detecting devices exceeds the SIC receiver optimum power levels, which are 3 levels in this paper. To compute the threshold $\gamma\prime$ in (4) for a desired probability of false alarm P_{FA}, which occurs when deciding $\mathcal{H}_N$ if the test in (4) is greater than the threshold $\gamma\prime$, so that P_{FA} can be written as

$$P_{PF} = p(T(\mathbf{y}) > \gamma\prime). \tag{5}$$

Since the test in (4) under both hypothesis is a Gaussian distribution, that $T(\mathbf{y}) \sim \mathcal{N}(\sum_{l=0}^{L-1}\sum_{n=1}^{N-1}\mathbf{s}_n, \frac{\sigma^2}{L})$ under $\mathcal{H}_{N-1}$ and $T(\mathbf{y}) \sim \mathcal{N}(\sum_{l=0}^{L-1}\sum_{n=1}^{N}\mathbf{s}_n, \frac{\sigma^2}{L})$ under $\mathcal{H}_N$, we rewrite (5) as

$$P_{FA} = Q\left(\frac{\gamma\prime - \sum_{l=0}^{L-1}\sum_{n=1}^{N}\mathbf{s}_n}{\sqrt{\frac{\sigma^2}{L}}}\right) \tag{6}$$

Thus the threshold $\gamma\prime$ is given by

$$\gamma\prime = Q^{-1}(P_{FA})\sqrt{\frac{\sigma^2}{L}} + \sum_{l=0}^{L-1}\sum_{n=1}^{N-1}\mathbf{s}_n \tag{7}$$

Following the same steps, the probability of detecting the number of active devices is

$$P_D = Q\left(\frac{\gamma\prime - \sum_{l=0}^{L-1}\sum_{n=1}^{N-1}\mathbf{s}_n}{\sqrt{\frac{\sigma^2}{L}}}\right) \tag{8}$$

From (7) and (8) the probability of detection P_D can be written as a function of signal to noise ratio SNR

$$P_D = Q\left(Q^{-1}(P_{FA}) + \frac{\sum_{l=0}^{L-1}\sum_{n=1}^{N}\mathbf{s}_n - \sum_{l=0}^{L-1}\sum_{n=1}^{N-1}\mathbf{s}_n}{\sqrt{\frac{\sigma^2}{L}}}\right). \tag{9}$$

The probability of correct detection of the number of active users as a function of the SNR for P_{FA} = 0.1 is shown in Fig.3. Observe that the detection performance increases monotonically and smoothly with increasing SNR.

V. Simulation Results

In this section, the simulation results are presented to evaluate the throughput and channel access delay performance of the BF-SA-NOMA protocol. Throughout the simulation, we assume there is one IoT gateway with N_r receiving antennas and a total of *M* IoT devices each with N_t transmitting antennas. A binomial distribution is considered to model the random number of active IoT devices *N*, each with probability of transmission p_{τ}.

$$P_T(N; p_{\tau}, M) = \binom{M}{N} p_{\tau}^N (1 - p_{\tau})^{M-N} \tag{10}$$

Fig. 4 shows the throughput of BF-SA-NOMA for different values of probability of transmission p_{τ}, when *M*=60, N_t=2, N_r=2, *m*=3 optimum power levels and *k*=3 attempts for the random selection of distinct optimum power levels. In the simulation, throughput is defined as the average number of packets that are successfully decoded for a given probability of transmission. As expected, we can observe that the throughput decreases as the probability of transmission increases. Also, we can see that the throughput of the BF-SA-NOMA protocol is always higher than that of Aloha-NOMA and conventional SA protocols. In particular, when the probability of transmission is 0.15, the throughput of BF-SA-NOMA is almost 60 times higher than that of conventional slotted Aloha and 2 times higher (i.e., the beamforming gain) than Aloha-NOMA. This demonstrates that BF-SA-NOMA provides a dramatic improvement in throughput in comparison

$$\frac{p(\mathbf{y};\sum_{n=1}^{N}\mathbf{s}_n,\mathcal{H}_N)}{p(\mathbf{y};\sum_{n=1}^{N-1}\mathbf{s}_n,\mathcal{H}_{N-1})} = \frac{exp[-\frac{1}{\sigma^2}(\mathbf{y}-\sum_{n=1}^{N} h_n\mathbf{s}_n)^T(\mathbf{y}-\sum_{n=1}^{N} h_n\mathbf{s}_n)]}{exp[-\frac{1}{\sigma^2}(\mathbf{y}-\sum_{n=1}^{N-1} h_n\mathbf{s}_n)^T(\mathbf{y}-\sum_{n=1}^{N-1} h_n\mathbf{s}_n)]} \lessgtr_{\mathcal{H}_{N-1}}^{\mathcal{H}_N} \gamma, N=1,...M. \tag{3}$$

$$T(\mathbf{y}) = \frac{1}{L}\sum_{l=0}^{L-1}\mathbf{y} \lessgtr_{\mathcal{H}_N}^{\mathcal{H}_{N-1}} \frac{2\sigma^2\ln\gamma - ((\sum_{n=1}^{N-1} h_n\mathbf{s}_n)^T(\sum_{n=1}^{N-1} h_n\mathbf{s}_n) + (\sum_{n=1}^{N} h_n\mathbf{s}_n)^T(\sum_{n=1}^{N} h_n\mathbf{s}_n))}{-2(\sum_{n=1}^{N-1} h_n\mathbf{s}_n + \sum_{n=1}^{N-1} h_n\mathbf{s}_n)} = \gamma\prime. \tag{4}$$

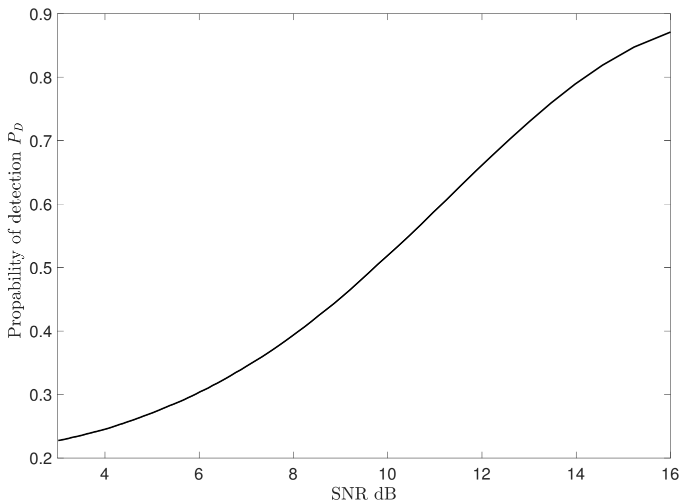

Fig. 3. Probability of detection as a function of SNR

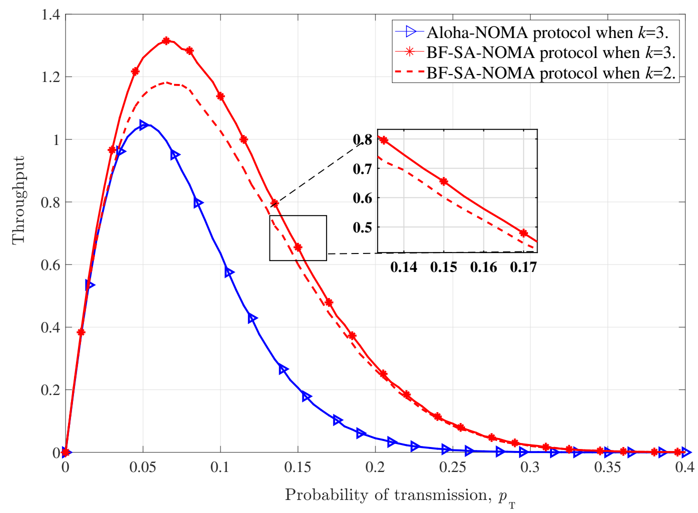

Fig. 5. Throughput of BF-SA-NOMA VS. Aloha-NOMA for different values of probability of transmission when M=60, m=3, k=2 and 3 attempts, N_t=2 and N_r=2.

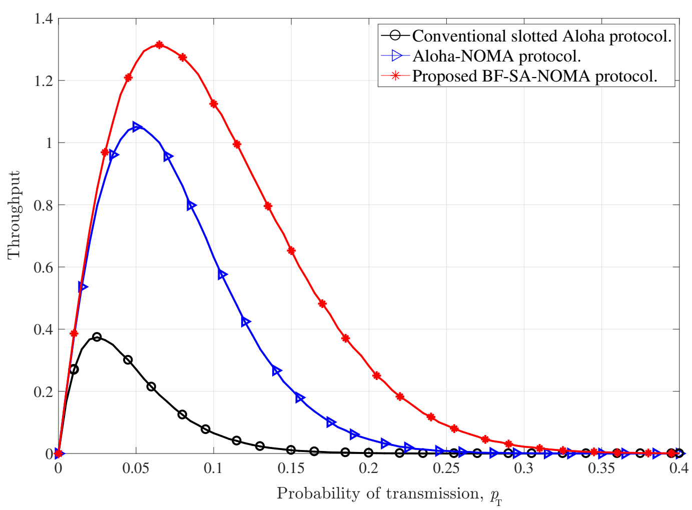

Fig. 4. Throughput of BF-SA-NOMA VS. Aloha-NOMA and conventional slotted Aloha protocols for different values of probability of transmission when M=60, N_t=2, N_r=2, m=3 optimum power levels and k=3 attempts.

with conventional slotted Aloha and Aloha-NOMA protocols due to the additional "virtual" sub-channels in the spatial and power domains. More importantly, it is worth mention that achieving a throughput gain similar to that of the proposed BF-SA-NOMA using Aoha-NOMA requires an excessive increase in SIC power levels which is impractical when using power-limited IoT devices.

In Fig. 5 and Fig. 6 we show the beamforming gains in terms of the channel access delay and throughput of BF-SA-NOMA for different values of probability of transmission when k=2,3 attempts, N_r=2, N_t=2, M=60, and m=3 optimum power levels. In simulation, the channel access delay is composed of three components, namely: round trip delay, delay due to the attempts for random selection of distinct power levels, and the back-off delay (that occurs at the event of the number of active IoT devices is greater than the degree of SIC receiver or when the IoT devices fail in selecting distinct optimum power levels in k attempts). Fig. 5 and Fig. 6 illusrates the beamforming gains, where it is shown that BF-SA-NOMA when k=2 can still achieve a higher throughput than Aloha-NOMA when k=3 with a lower channel access delay resulting from reducing the probability of collision and the average back-off delay by creating more virtual sub-channels via MIMO beamforming.

In order to see the impact of the number of optimum power levels on the throughput of BF-SA-NOMA, we show the throughput of BF-SA-NOMA for different power levels in Fig. 7. For M=60, k=2, 3 and 5 and probability of transmission of 0.05, the throughput of Aloha-NOMA increases with the increase in optimum power levels (SIC degree). For example, Aloha-NOMA with 3 power levels has a higher throughput than Aloha-NOMA with 2 power levels. However, the throughput improvement becomes insufficient for optimum power levels greater than 5 (saturation in the throughput gain). Also, the simulation results in Fig. 5, shows the impact of the number of attempts k, for picking distinct optimum power

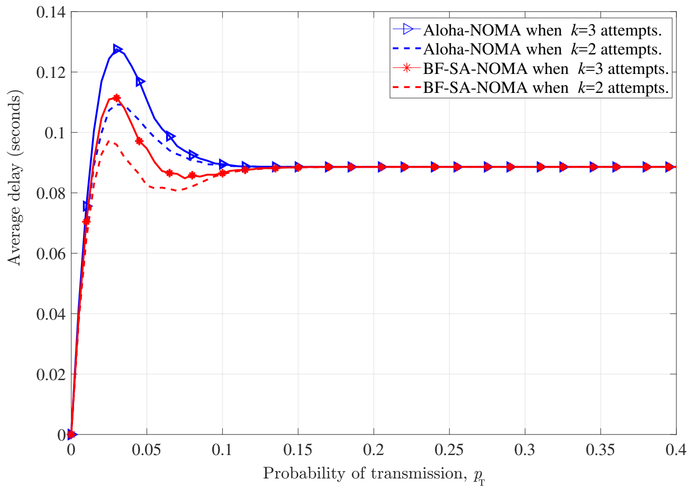

Fig. 6. Average delay of BF-SA-NOMA VS. Aloha-NOMA for different values of probability of transmission when M=60, m=3, k=2 and 3 attempts, N_r=2 and N_t=2.

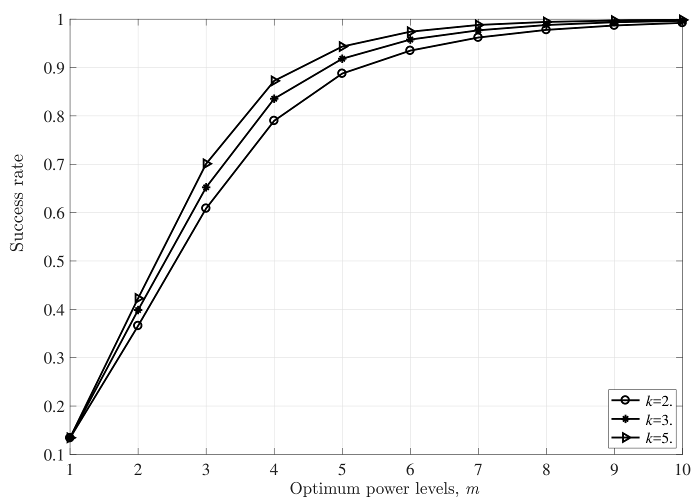

Fig. 7. Throughput of BF-SA-NOMA for different values of optimum power level m when M=10, N_t=2, N_r=2 and k=2, 3 and 5 attempts.

levels, on throughput for different optimal power levels. The more attempts allowed for picking the optimum power levels, the higher the throughput that can be achieved at the cost of increased delay.

VI. Concluding Remarks

In this paper, we propose BF-SA-NOMA as a random access protocol that is easy to implement, scalable and compatible with the limited-power and low complexity requirements of IoT devices. The proposed protocol has three major advantages: (*i*) it uses a form of multiple hypothesis testing at the IoT gateway to determine the number of active IoT devices in the medium. Knowing the number of active IoT devices is essential for optimizing the SIC power levels in order to distinguish between signals transmitted from different IoT devices on the same time and frequency, (*ii*) BF-SA-NOMA demonstrates a significant improvement in throughput for a large number of IoT devices, compared with conventional slotted Aloha and Aloha-NOMA protocols, through the exploitation of power and spatial domains without excessively increasing the SIC power levels which is impractical when using power-limited IoT devices, and (*iii*) it addresses the Aloha-NOMA channel access delay problem by reducing the probability of collision and consequently lowering the average back-off delay via beamforming. Simulation results has shown that BF-SA-NOMA can achieve higher throughput than Aloha-NOMA with fewer attempts and consequently a lower channel access delay. Such a random access protocol can be quite important for massive M2M communication in IoT networks. Future work will consider fairness and power consumption analysis of IoT devices using the proposed protocol and will address a comparison with protocols based on Listen Before Talk (LBT) techniques, which are often referred to as carrier sense multiple access (CSMA) protocols.

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