ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

SELF - ORGANIZED NETWORK MANAGEMENT MODEL FOR NEXT GENERATION WIRELESS HETEROGENEOUS SYSTEMS

M.Sc. THESIS

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Department of Computer Engineering

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YENİ NESİL KABLOSUZ ÇOKTÜREL SİSTEMLERDE KENDİNİ DÜZENLEYEN AĞ YÖNETİM MODELİ

YÜKSEK LİSANS TEZİ

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Özgür Umut AKGÜL, a M.Sc. student of ITU Graduate School of Science Engineering and Technology , student ID 504111526 successfully defended the thesis entitled **"SELF - ORGANIZED NETWORK MANAGEMENT MODEL FOR NEXT GENERATION WIRELESS HETEROGENEOUS SYSTEMS"**, which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family,

FOREWORD

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ABBREVIATIONS

LTE	**:** Long Term Evolution
QoS	**:** Quality of Service
OPEX	**:** Operational Expenditures
CAPEX	**:** Capital Expenditures
SON	**:** Self-Organizing Network
IC	**:** Integrated Circuit
TBD	**:** Trigger Based Devices
PSD	**:** Periodic Signal Devices
TCD	**:** Throughput Concerned Devices
SoT	**:** Self Organized Things
I2gSON	**:** Immune Inspired green Self-Organized Network
MHC	**:** Major Histocompatibility Complex
SCBS	**:** Small Cell Base Station
MBS	**:** Main Base Station

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SELF - ORGANIZED NETWORK MANAGEMENT MODEL FOR NEXT GENERATION WIRELESS HETEROGENEOUS SYSTEMS

SUMMARY

Increase in mobile devices and RF applications, triggered a bottleneck in the throughput and coverage. Even though the carrier aggregation solved the capacity problems, the quality of service (QoS) decreased tremendously in terms of peak data rates and latency. Providing an effective solution, LTE-A, which integrates the full-frequency reusing scenarios, is proposed. By this way, the idea of micro and femto cells is developed. These small cells are relatively low powered, capable of handling lower number of users and have smaller coverage areas. However, the heterogeneity of networks increased the interference problems interference and eventually resulted in resource allocation problems. Another applied solution to this capacity need is to increase the transmission power of the main base stations. As a general knowledge, it is known that increasing transmission power always increases the throughput. Based on this fact, higher capacity wireless links that consumes higher energy are designed. Both the small cell solution and the higher powered wireless link solution increase the energy consumption of the network. This high power dissipation pointed the tradeoff between energy efficiency and spectral efficiency. The higher power dissipation causes higher operational costs and electronic aging problem, which eventually increases the CAPEX. Due to this, energy optimization algorithms, which can decrease energy consumption while maintaining performance of the network, are investigated. The researches showed that the most of the energy consumption is due to the dynamic nature of the daily traffic. Over providing the network, which eventually causes resource mismanagement, solves the wireless links lack of ability of adaptation to the network's dynamic nature. Self-organizing networks are capable of following the dynamic nature of the network. Using its three predefined bloc, i.e. self-configuration, self-optimization and self-healing, it can adapt itself to the traffic changes and also needs more human intervention.

Even though, the development of self-organizing network structure decrease the visibility of the trade off between spectral energy and energy efficiency, the deployment of a new user type bring out the previous problems. The developments in very and ultra large-scale integration and the decrease in the integrated circuit prices caused the spread of consumer electronics that contains RF modules, namely "things". These thing devices (TD) produce large amount of data that are gathered from their environment based on their work definitions. The idea of connecting these TDs created the concept of Internet of Things (IoT). However, these new type of users are different from the existing mobile users. They have different QoS requirements and performance metrics. For most of the devices, the latency and jitter are not a realistic problem and they have no throughput concerns. However, they try to optimize their energy consumption over a large period. Due to this reason, they can be classified as a hybrid structure that exists between mobile devices and sensor nodes. The existing self-organizing network deployments are incapable of handling these

devices as the existing network management topologies give particular importance to the optimization of the network QoS, which is not valid for TDs. For most of the network management deployments, the applied most optimal network deployment is the worst network topology for IoT networks. The Ad-Hoc algorithms and scheduling algorithms are maintaining the topology management frameworks so far. However, the increasing interactions between these two different user types, i.e. TDs and mobile users, brought the necessity of a complete architecture that can handle both of the users. In this study, a self-organized network management framework that can handle the hybrid user types is proposed. During the development phase of this management framework, we have designed two different network management frameworks for two different homogenous networks.

First, we have developed an immune inspired green self-organizing network (I^2gSON) controller that handles the throughput-concerned mobile users. During this study, we inspired from the immune system concepts and redefined the self-organizing network blocks using immune system features. More specifically, we inspired form B-cell, T-cell, Thymus and antigen concepts and mapped them to the self-configuration, self-optimization, self-healing and low energy efficiency concepts, respectively. The considered network topology consists of small cells and the users. The proposed framework is designed for the main base station structures of the network. The proposed framework uses three actions in the self-configuration block and tries to decrease the power consumption while maintaining the acceptance ratio of the base stations. By the end of the simulations, we observed that the proposed framework stabilizes the energy consumption of the network while increasing the acceptance ratio by 26%. Our second design proposes a self-organizing framework for IoT devices. In this study, we divided the TD types into two, i.e. trigger based devices (TBD) and periodic signaling devices (PSD). The proposed framework looks into the problems of coverage, energy efficiency for IoT. The self-organizing framework of this study decreases the human intervention. We explore first a tradeoff between the coverage and energy demands through simulation studies. Then, we defined two decision metrics, called as conflict and spatial parameters that are used to tune the extent of coverage and region of overlap. Both of these parameters are utilized for network management in self-optimization process. In addition, we develop a sleep mode optimization technique in order to minimize the energy consumption and stabilize the battery lifetime, which is a novel approach that considers the spatial distributions. These results showed that this technique provides 150% increase in durability with 220% increase in the overall lifetime. Finally, using these two different frameworks we proposed a novel hybrid topology management framework that can handle both IoT devices and mobile users. Developing this study, we used the strongholds of each framework and integrated them. We defined three-operation policy that effects the network deployment, i.e. high performance (HP), most energy efficient (MEE) and balanced system (BaS). The mobile user network topology is decided according to the active policy that is determined by the time of the day. IoT deployment is determined using the previously explained self-organizing framework. We used a weighted approach to determine the event probability and to maintain a higher event observation rate. In order to integrate this weighted approach, the network is divided into three subgroups. The simulation results proved that the proposed network could handle both IoT devices and mobile users and maintain high performance with a high-energy efficiency.

YENİ NESİL KABLOSUZ ÇOKTÜREL SİSTEMLERDE KENDİNİ DÜZENLEYEN AĞ YÖNETİM MODELİ

ÖZET

Son yıllarda artan mobil cihaz kullanımı ve beraberinde getirdiği yüksek ağ trafiği, iş çıkarımı ve gecikme problemlerini gündeme getirmiştir. Kullanıcı paketleri giderek artan bir gecikme ve seğirme ile karşılaşmaya başlamış ve bunun neticesinde iş çıkarımı aşırı düzeyde düşmüştür. LTE sistemlerinin geliştirilmesi ve uygulamaya alınmasıyla birlikte frekansların tekrardan kullanımı ve taşıyıcı birleştirme fikirleri gündeme gelmiştir. Ancak taşıyıcı birleştirme ağ kapasitesinde aktif bir uygulama olmakla birlikte güç tüketimi konusunda kayda değer bir gelişme sunamamıştır. Güç tüketimi bakımından frekansların tekrar kullanılabilirliği ve beraberinde getirdiği küçük ağ yapıları fikri nispeten daha parlak sonuçlar yaratmıştır. Temel olarak, daha sınırlı alanlarda daha düşük güçte baz istasyonları kurularak aynı frekansların kullanılması fikrine dayanan bu yöntem, kullanıcıyla olan mesafenin az olmasından dolayı güç tüketiminde azalma getirmiştir. Ancak küçük ağ sistemlerinin kullanımlarının yaygınlaşmasıyla birlikte, farklı ağların birbirine yaptığı girişim giderek artmıştır. Artan girişim problemi netice itibariyle güç tüketiminde azımsanmayacak bir artışa neden olmuştur. Aynı zamanda, ağ yapısının heterojen özellik kazanmasıyla birlikte kaynak atama da giderek zorlaşan bir alan olmuş ve netice itibariyle hem sermaye harcamalarını hem de işletim masraflarını arttırmıştır. Bu süreçte, kapasite artışını kontrol etmek için uygulanan bir diğer yöntem ise ağ içerisindeki baz istasyonunun yayın gücünü arttırmaktır. Felsefe olarak, baz istasyonunun yayın gücünün artması beraberinde ağın iş çıkarımının artmasını tetiklemektedir. Bu felsefeye dayanarak daha yüksek kapasiteye sahip, çok daha yüksek güç tüketimi olan kablosuz ağ bağlantı noktaları geliştirilmiştir.

Ancak güç tüketimindeki aşırı artış, artan girişim problemi nedeniyle iş çıkarımında kısıtlı miktarda bir artış sağlarken, hem işletim maliyetlerinin hem de elektronik yaşlanmanın artmasına neden olmuştur. Bu yaşlanma problemiyle cihazların kullanım ömürleri ciddi miktarda azalırken sermaye masrafları da üssel olarak artmıştır. Uygulanan bu yöntemler ağ performansı ile güç tüketimi arasındaki ödünleşimi keskin bir şekilde ortaya koymuştur. Bu nedenle performans bakımından üstün olan ağ yönetim sistemlerinde, güç tüketimini iyileştirmek için ilave yöntemler araştırılmaya başlanmıştır. Bu araştırmalar göstermiştir ki güç tüketimindeki problemlerin başlıca nedeni yönetim sisteminin gün içinde sıklıkla değişen trafik akışını takip edememesidir. Bu nedenle ağ sistemleri genellikle ağa fazlaca kaynak sunmakta bu da güç tüketiminde ciddi artışa neden olmaktadır. Kendini düzenleyen ağ yönetim mekanizması gün içerisinde aktif olarak değişmekte olan trafik ve ağ koşullarının yönetim mekanizmasınca etkin bir şekilde kontrol edilerek, ağ yapısının en verimli yapıya getirilmesini sağlamaktadır. Bu en iyileme işlemi kendini düzenleyen ağ yönetim sistemlerinde tanımlanmış olan üç adet temel yapıya dayanmaktadır. Bu yapılar kendini ayarlama, kendini en iyileme ve kendini iyileştirmedir. Ağ yapısındaki bu ödünleşimin görünürlüğü, kendini düzenleyen ağ yapısının geliştirilmesiyle birlikte

azalmıştır. Ancak bu ödünleşim, yeni bir kullanıcı yapısının geliştirilmesiyle birlikte yeniden görünür hale gelmiştir.

Tümdevre tasarımında ve gerçeklenmesinde ortaya çıkan ilerlemeler çok daha gelişmiş ve verimli sistemlerin hem daha ucuza hem de daha küçük boyutlarda yapılmasını sağlamıştır. Bu durum ise günlük hayatta sıkça kullanılmakta olan kullanıcı cihazlarına RF alıcı ve vericilerinin eklenmesine olanak sağlamıştır. Bu cihazlar gün içerisinde oldukça fazla miktarda veri oluşturmakta ve bu verileri kendi iş tanımlarına göre belli birimlere iletmektedirler. Bu cihazların RF yapıları taşımasıyla birlikte, bu veri akışını sağlamak için birbirlerine bağlanması fikri ortaya çıkmıştır. Bu şekilde, cihazların ağı (CA) fikri ilk defa ortaya atılmıştır. Bu yeni ağ yapısının geliştirilmesiyle birlikte ortaya daha önceden var olmayan yeni bir kullanıcı tipi çıkmıştır. Klasik mobil kullanıcıdan farklı olarak, gecikme ya da seğirme konusunda herhangi bir performans beklentisi olmayan bu cihazlar açısından, en önemli kriter güç tüketimidir. Bu bakımdan geliştirilmiş olan bu yeni kullanıcı türü mobil kullanıcılarla duyarga cihazlarının arasında bir yapıya sahiptir. Ancak var olan kendini düzenleyen ağ yönetim modelleri önceliği ağın servis kalitesini en iyilemeye ayırdıklarından, yeni gelişmiş olan cihazlar açısından yetersiz kalmışlardır. Şu anda günlük cihaz yönetiminde genellikle doğaçlama yöntemler ve duyarga ağlarında kullanılmakta olan algoritmalar kullanılmaktadır. Ancak günlük cihaz ağıyla mobil kullanıcı ağlarının arasındaki etkileşimlerin artması beraberinde her iki kullanıcıyı birlikte kontrol edebilen sistemlerin geliştirilmesi ihtiyacını doğurmuştur. Bu tez kapsamında her iki kullanıcı modelini de etkin bir şekilde yönetebilecek kendini düzenleyebilen ağ yapısı önerilemektedir. Bu amaçla iki farklı kullanıcı için ayrı ayrı performans beklentilerini karşılayabilen birer ağ kontrol sistemi geliştirilmiş olup, arkasından bu iki model birleştirerek, her iki kullanıcı modeline de yüksek performansla hizmet sunabilen bir yapı geliştirilmiştir.

Bu amaçla öncelikle doğadan esinlenilerek, kendini düzenleyen ağ yapısı geliştirilmiştir. Bu yapıda basitlik ve etkin olma özelliklerinin yanı sıra güçlü bir bellek yönetimi özelliğine sahip olmasından dolayı bağışıklık sistemi model alınmıştır. Tasarım süresinde bağışıklık sistemindeki B-hücresi, T-hücresi, Timüs organı ve antijen yapılarından esinlenilerek önerdiğimiz kendini düzenleyen yapının kendini ayarlama, kendini en iyileme, kendini iyileştirme ve problem tespiti kısımları tasarlanmıştır. Önermekte olduğumuz yapı, pek çok küçük ağ taşıyan bir ağı yönetmekte olan ana baz istasyonları için tasarlanmıştır. Küçük ağ baz istasyonları, haberleşme için kullanmakta oldukları gücü ve kullanıcı sayısını ana baz istasyonuna yollamaktadırlar. Verilen bu değerlere göre ana baz istasyonu, küçük ağ baz istasyonunun enerji verimini incelemekte ve verimsiz olduğuna karar vermesi durumunda daha önceden tanımlanmış olan üç farklı yöntemden birini olasılıksal olarak seçmektedir. Uygulanan yöntemin uygunluğu, T-hücresinden esinlenilmiş olan kendini en iyileme birimi tarafından incelenmekte ve bunun geçerli bir yöntem olup olmadığına karar verilmektedir. Verimin uygun olduğuna karar verilmesi halinde, karşılaşılan ağ sorunuyla uygulanan yöntem birbiriyle eşleştirilerek saklanmaktadır. Eğer uygun olmadığına karar verilirse, bu eşleştirme kaldırılmakta ve böylece etkin olmayan yöntem elenmektedir. Bu yöntem neticesinde en uygun çözümleri taşıyan yapıların oluşması sağlanacaktır ki; bu da bir sonraki hedefimiz olan hizmet alanındaki iyileşmeyi önümüze getirmektedir. Timüs organından esinlenilmiş olan kendini iyileştirme yapısı ağ yönetiminin politikasına karar vermekte ve bu politikaya göre sorunlu durumları belirlemektedir. Tez kapsamında aynı zamanda Markov yapısı

sunulmuş olup kararlı bir yapıda baz istasyonlarının hangi metotları aktif bir şekilde kullanacakları incelenmiştir. Benzetim sonuçları ortaya koymaktadır ki; önerilmiş olan yapı enerji tüketimini düzenleyip ağdaki yük dağılımını iyileştirirken, ağa kabul oranında % 26 bir iyileşme sunmaktadır.

İkinci olarak, günlük ağ cihazları için kendini düzenleyebilen bir sistem önerilmiştir. Bu yapıda ağın güç tüketiminin daha verimli bir hale getirilmesi hedeflenmiş olup bu amaçla kullanılmayan cihazların uykuya yatırılması esasına dayanan bir en iyileme tekniği geliştirilmiştir. Bu yapı içerisinde öncelikle gözlenilmesi beklenen olay yoğunluğu kullanılarak, aktif olması gereken cihaz sayısına karar verilmiştir. Hesaplanan bu cihaz sayısı hedeflenen olay yoğunluğunu gözlemlemek için kullanılması gereken cihaz yoğunluğudur. Bu yoğunluğun hesaplanması sırasında aktif kapsama alanı denilen bir katsayı tasarlanmış ve böylece aynı alanı kapsayan cihazların bu hesaplamada hata oluşturması engellenmiştir. Cihazların açık ve kapalı olacakları aralıkların belirlenmesi sırasında, çakışma katsayısı ve uzaysal bağıntıların yerel bilgisi kullanılmıştır. Çakışma katsayısı cihazın başka cihazlar tarafından kapsanmayan bölgeleri ne kadar kapsadığına göre hesaplanmakta ve bu şekilde bir liste yapılmaktadır. Öncelikle, en yüksek çakışma katsayısına sahip cihazlar aktif hale getirilirler. Yeterli cihaz sayısına ulaşılamaması durumundaysa uzaysal bağıntıların yerel bilgisi kullanılır. Uzaysal bağıntıların yerel bilgisi ile cihazların geriye kalan cihazlara olan uzaklıkları temel alınarak bir sıralama yapılır ve diger aktif cihazlara en uzak olan cihazlar aktif hale getirilerek, gerekli olan diğer cihazlar çalıştırılırlar. Yapılmış olan benzetimler süresince toplamda yetmiş adet cihaz için ağ yapısı incelenmiş olup, neticede hem cihazların ömürleri hem de sürdürülebilirlikleri gözlemlenmiştir. Cihazların ömürleri güçlerinin bittiği zaman olarak belirlenmiş olmakla birlikte, sürdürülebilirlik sınırı, cihazların toplam kapsama alanının %30 oranında düştüğü nokta olarak belirlenmiştir. Netice itibariyle sürdürülebilirlik anlamında %150 gibi bir artış gözlenirken, cihaz ömrü anlamında %220 lik bir artış sağlanmıştır.

Daha önceden de anlatıldığı gibi, bu tezin kapsamındaki en temel amaç farklı kullanıcı tiplerinin haberleşmelerini yani hem günlük cihaz haberleşmesini hem de klasik mobil kullanıcı haberleşmesini kontrol edebilen bir ağ yönetim yapısının gerçeklenmesidir. Bu amaçla, daha önceden tanımlamış olduğumuz bağışıklık sisteminden esinlenilmiş kendini düzenleyebilen ağ yapısı ile kendini düzenleyebilen cihazlar yapısını birleştirmiş bulunmaktayız. Bu çalışmada daha önceki çalışmalara ek olarak üç farklı ağ politikası tanımlanmıştır. Bunlar en yüksek performans politikası, en enerji verimli çalışma politikası ve dengeli çalışma politikası olarak gruplandırılabilirler. Bu politikalar yardımıyla gün içerisinde özellikle mobil kullanıcıların beklentisinde ortaya çıkan değişiklikleri takip edebilen bir ağ yapısı tasarlanmıştır. Bunun yanı sıra olay yoğunluğu hesaplanırken, ağırlıklı olasılık fonksiyonu kullanılarak daha fazla olay görülen bölgelerde daha fazla cihazın çalıştırılması sağlanmıştır. Bu ağırlıklı çalışma yönteminin işler hale gelebilmesi için, ağ yapısı temel olarak üç ana kısma bölünmüş ve cihaz yaşam süresindeki incelemeler bu üç ana bölgede farklı olay sıklıklarıyla gerçeklenmiştir. Gerçekleme sonuçları göstermektedir ki, önermekte olduğumuz yöntem karışık kullanıcı çeşitlerini başarılı bir şekilde kontrol edebilmektedir. Tasarımımızın direkt olarak baz istasyonlarını hedef alması, hem kurulum hem de işletim alanlarında ekonomik kazançlar sağlaması ve performanslarda ilerleme oluşturması nedenleriyle özellikle telekomünikasyon şirketleri tarafından kullanılacağı düşünülmektedir. Öte yandan daha gelişmiş haberleşme sistemleri ile

hem kullanıcılara sunulan hizmet kalitesi arttırılacak hem de enerji tüketimini ve böylece CO_2 salınımını azaltarak çevreye verilen zarar önlenecektir.

1. INTRODUCTION

The tremendous increase in the number of consumer electronics and the improved communication trend has triggered a new challenge, high traffic. Increase in video and sound traffic caused an exponential increase in the peak data rates, which eventually caused Quality of Service (QoS) concerns. A service provider has to increase the capacity of the network while decreasing the latency and the jitter that a packet has faced. Deployment of Long Term Evolution-Advanced (LTE-A) systems is proposed to provide these requests. However, LTE-A brought out newer challenges. First problem is the allocation of the frequencies with in the same wireless network, which is a natural result of picocell and femtocell usage. Picocells and femtocells are small powered base stations that have low coverage area. The main idea behind the usage of small cells (picocell + femtocell) is the belief that using the same communication frequency for different users within different small cell will solve the increasing capacity demand. However, this distributed structure of the network uncovered another challenge, interference. Small cells and their users that are using the same communication frequency could interfere each other. The uplink and downlink interference problem caused low throughput ratio and eventually low QoS. In a broader vision the application of LTE-A made the resource allocation problem more visible within the same wireless network.

Another significant challenge in LTE-A is the energy problem. Based on the fact that increasing transmission power always increases the throughput, highly power-consuming devices are implemented. The design and implementation of advanced and more powerful wireless links to overcome the residual capacity demand enhanced the total power dissipation in the communication backhaul. This increase in the total energy dissipation in communication has effects on each layer of the society. In terms of engineering, the trade off between spectral efficiency and energy efficiency became acutely visible. Increasing transmission power increased the throughput. Nevertheless, this increased power and the increased current flow within the electronic

circuits of wireless links smoked out the aging problem of the electronic components. Due to this aging problem, the device durability diminished immensely. In terms of network provider, the high power consumption hiked the operational expenditures (OPEX). Besides, to maintain perpetual service, unusable or “dead” links needed to be changed and newer small cells needed to be implanted, which increased the capital expenditures (CAPEX). Addition to the economical aspects, being depended to human force is another back draw. From setup to failure recovery, in each stage human force becomes a necessity. Another important effect of high-energy communication is in the political field. The European Union Energy Policy forces the governments to support green systems. All this effects compels the network providers to decrease the total power consumption on communication.

However, the mentioned spectral efficiency and energy efficiency tradeoff causes a dilemma. If the network providers increase their transmission power, the throughput will increase, QoS will increase and eventually the number of users will increase. However, the explained issues about the energy consumption will be remain unsolved and cause critical problems in the medium and long term. Nevertheless, if the providers decrease their transmission power, the throughput will decrease, QoS will decrease and in the end the number of users will decrease. This dilemma pushed the network providers to support the researches on the multi-cell power control and optimization frameworks, which could be a “midway solution". These researches showed that for a network structure to increase the energy efficiency, applying a basic energy saving algorithm would not be sufficient. This is mostly because the network providers’ over provision of the network resources according to the peak hour network utilization [1]. However, this over provision causes a mismatch between maximum network utilization and average network utilization. This wrong policy in resource management consequentially causes low energy efficiency. So to increase the energy efficiency, the network capacity should be dynamically changed to match the traffic needs without over provision the network, which finally leads the design of Self-Organizing Networks (SON) [2]. Using its three defined block, i.e. Self-Configuration, Self-Healing and Self-Optimization, SON deployments presents a dynamic and autonomous topology management framework that can adapt the network based on the traffic demands. As the network resources can be organized based on the active needs, the energy efficiency

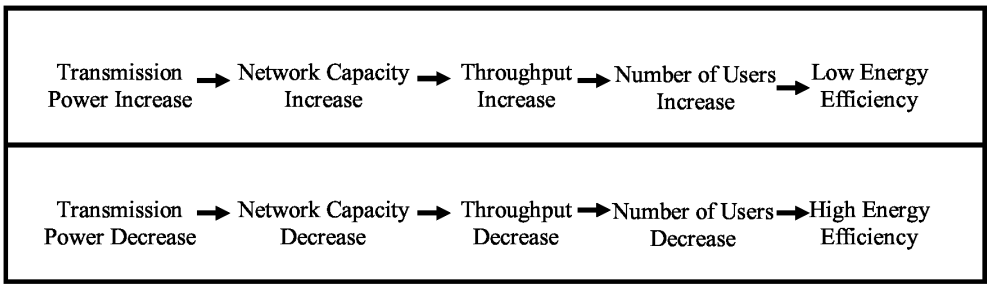


Figure 1.1: Performance-Energy Efficiency Tradeoff.

is highly maintained. Even though the visibility of the performance-energy trade-off decreases, deployment of a new user type revealed the severity of this trade-off along with newer challenges.

Up till now the defined network contains many kind of users with QoS expectations, usually with throughput and jitter concerns. However with the evolvement of cheaper and easier electronic devices and the improvements in the Integrated Circuit (IC) design, number of consumer electronics containing an RF module increased incredibly. Many social aspects like increasing daily life comfort or danger management brought the idea of connecting these electronic devices, things, and communicating them. The Internet of Things (IoT) concept created a new user type, which stands in the middle between mobile users and sensor devices in the wireless network. Unlike the usual mobile users, thing devices do not present any actual QoS requirements. Even though they produce immense data and transmit this data to users or other thing devices, the jitter or the throughput is not actual concerns. What is more important for thing devices is the durability, as most of them are using batteries. Even though there exist many different kinds of electronic devices in the thing concept, they can be divided into two main categories, Trigger Based Devices (TBD) and Periodic Signal Devices (PSD). TBDs are more like a sensor devices that observes the occurrence of a specific event while PSDs collects more specific details of the observed event. For example TBDs are like a motion sensor that sends an alarm stating there exist an event if it captures any motion while PSD sends a complete knowledge about the motion like the velocity, the acceleration vector or the direction. The definition of event highly depends on the type of the electronic device.

In a more general perspective, the IoT network management challenge is more likely "the tip of an iceberg" because the proposed solutions are usually specific IoT solutions

without considering any mobile users. However, these two different user types usually coexist in the same wireless network. A practical solution can be using two different structures like two different base stations to optimize each user type differently but such a structure is inefficient due to many economical and engineering problems. Gathering separated network solutions for IoT and mobile users in the same base station can be another alternative solution, however, the complexity of the base station will increase exorbitantly. High complexity causes high-energy consumption and makes the system open for failures. Low energy efficiency triggers both economical impacts and aging problem, which leads enormous decrease in durability. Eventually, the network becomes inoperable. Based on this fact, a topology management framework that can cope with different users with variable performance metrics needs to be designed.

1.1 Purpose of Thesis

In this thesis, the main objective is to overcome the performance and energy efficiency trade-off in the next generation LTE-A by designing an energy efficient topology management framework that can cope with the coexistence problem of users' different performance metrics. With this purpose, an immune inspired SON framework using spatial correlation for network optimization is presented. To specify the topology management specifications, two special attributes of the proposed system are investigated separately and their strongholds and weaknesses are marked. The hybrid SON model that uses the strongholds of both frameworks is presented in chapter 4. The outcomes of this thesis can be itemized as;

- An immune system inspired self-organizing network framework is designed that can maintain the network wide energy efficiency while pursuing the high network performance in terms of throughput in a dense mobile user case.
- A Self-Organizing Things (SOT) framework is presented that configures the IoT network topology to the most efficient deployment in terms of lifetime.
- A novel usage of Local Indicator of Spatial Association is presented to measure the optimality of the SOT topology.
- Combining this two different topology management frameworks, a hybrid topology management framework that can handle both kind of users is presented.

1.2 Hypothesis

In this work, a network structure that contains both mobile users and "things" is considered. These users have their performance metrics and expect the network manager to maintain the optimum network topology that would provide fair and high quality service. The general expectations of the users are presented in Table 1.1.

Table 1.1: Different user models and their performance metrics.

	Mobile Users	Thing Devices
User Homogenity:	Homogen	Heterogen; TBD and PSD
Band Requests:	Variable	Variable and Constant
Communication Frequency:	Constantly	Rare
Major QoS concerns:	Throughput	Durability

As previously stated, 3 main framework is going to be presented to overcome the tradeoff between performance and energy consumption. Based on the user model the following assumptions can be made;

- Being simple is the key challenge in the SON design. As the complexity increases the total energy consumption increases, the network becomes open to failures and system becomes unstable easily,
- To achieve a high performance for mobile users, the main base station in the network should contain a memory and a efficient memory management structure to avoid the high energy consumption and complexity,
- PSDs rarely transmitting large band requests and the main objective is to increase the durability of device while keeping their throughput ratios. Based on this definition, it is possible to model PSDs as mobile devices with low communication rate,
- The events can be divided into two different types, discrete events and continuous events. Discrete events are like the alert of a coffee machine, initiating a discrete knowledge that is special for a specific region. However, the continuous events are like the motion, which repeats itself according to a specific cohesion through the time. For example the event of detecting a motion is a continuous event as motion is a vector and continues over time,

- TBDs tries to maximize their possibility of observing an event. To increase the observing change of discrete events the total coverage area should be maximized whereas to increase the change of observing as many continuous events as possible the TBDs should be placed to different and far locations.

In consideration of these assumptions, first two different frameworks for different user types are designed. In a mobile network, the anomalies and changes in the network topology should be followed and the network topology should be changed according to the latest state of the network. However, as explained earlier, even though SON is an efficient solution, many of the proposed frameworks are complex or inefficient due to wrong memory management. As a complex system increases high-energy consumption and latency, the applied structure should be simple and efficient in terms of acceptance rate. Addition to these more basic and efficient memory management framework is necessary. To propose a solution, we researched already existing biological structures that can solve the self-organization problem with a few simple instructions [3]. Immune system in human body, which is a great example for natural SON structure, has very low complexity and uses a simple memorization mechanism to perform efficient actions. Based on these reasons we mapped immune system in this thesis.

The network should automatically adapt itself to the topology changes and works with the highest possible performance rate. A self-organizing network topology management can solve the thing device's management and optimization problem [4, 5]. For IoT network, distribution of active TBDs is as important as the total coverage area. However, the existing solutions only considers the energy based scheduling without paying any specific attention to the event observation. Low event observation rate decreases the performance of the network and sharply presents the energy efficiency-performance trade-off. To increase the performance of IoT in terms of event observation, the total coverage area, distribution of devices and the distribution of the events should be taken into consideration while scheduling. Addition to this scheduling should be simple while maintaining low the organization communication rate between devices. By definition Local Indicator of Spatial Association (LISA) coefficient presents the knowledge about how a specific attribute changes over location

with a simple mathematical expression. Based on the data it presents and the simplicity we use LISA coefficient in the optimization process of the network.

2. IMMUNE INSPIRED GREEN SELF-ORGANIZING NETWORK

The recent raise in mobile traffic revealed a new challenging tradeoff between energy consumption and user service. In a dense network structure, the users transmit their bandwidth requests to the base stations and the base stations assigns specific bands to specific users. This "request-assignment" process brings out the concept of acceptance rate, which is defined as the number of accepted band requests of the user. The main objective of the network management so far is to increase the acceptance rate of the users as much as possible even though this implies inefficient energy management. Increasing the acceptance rate also presents the necessity of an increase in network capacity. To satisfy that rapidly growing energy-killer capacity needs, Self-Organizing Networks (SON), which is one of the core techniques proposed in LTE-A, can be seen as one of the promising area for the telecommunication operators. This has been the basic motivation behind the 3GPP LTE group, which aims to develop and design IP-based n-tier architecture to address the network operational efficiency. However, the increase in capacity without an efficient energy management, decreases the lifetime of the base stations and also increases the operating cost. In many cases, it is hard to conserve the acceptance rate while increasing the energy efficiency and have to choose one or other.

Low energy efficiency is usually because of the incapability of following dynamically changing network conditions [6]. The usually applied strategy is to increase the network resources to follow the increasing requests, which leads to the result of idle resources. This mismanagement of resources decreases the energy efficiency. In a network, anomalies and changes in the network topology should be followed and the network topology should be changed according to the latest state of the network [1]. The state of a network can be decided by the number of active femtocells and microcells and the number of users that are connected to them and the main base station. SON is a solution [5] but many proposed frameworks are complex or inefficient. As the complexity of the applied solution increases energy efficiency

decreases, latency increases and the aging problem of the electronic devices become a major problem. The used SON structure should be simple and efficient in terms of acceptance rate. As a solution to the inefficiency problem, memory is added to the SON framework to help it remember the previous state of the network and decide the optimum solution. However, the complexity of the framework increased as a memory management framework is added to the already existing structure. No matter how simple the applied memory management framework, the energy efficiency and the latency of the system continue to be problem as the applied memory management structure is an add-on to the already existing SON framework.

2.1 Purpose

A simple yet efficient network management framework should be designed with a strong memory management control. The biological systems can perform great tasks with simple instructions [1]. Based on this simplicity advantage, we researched the biological systems to find a system. Immune system, which is one of these systems become front among all other biological systems due to the its self sustained auto-configuration ability, simple but robust memory management ability and its improved stability and effectiveness. Here, the solutions and models inspired by the immune system for wireless networks create long-term solutions. In addition to the simplicity and effectiveness, the immune systems of body cells has the ability to adapt and immune itself to the anomalies, changing conditions and failures. As an objective of this study is to maintain stability, bio-inspired system helps us to achieve this objective naturally. The concept of bio-inspiration is basically mapping the natural concepts and using these concepts to solve a specific problem that can be solved by following a similar procedure in nature [3]. In this chapter, we are presenting an energy efficient and flexible immune inspired green SON ($I^2 - gSON$) structure that conserves and increases the performance while stabilizing the energy consumption. We are defining the SON concepts, self-organizing, self-healing and self-optimizing, using immune system concepts, B-cell, T-cell and antigen, respectively. Our main contributions can be presented under some major bullets.

- The high-energy consumption is modeled as an antigen. If the average energy consumption of base station exceeds a static threshold lastly accepted user is marked as an antigen.
- The self-learning concept in immune system is included in proposed framework. The memory concept stabilizes the fluctuations in energy and increases the response speed.
- We model the concept of B-cell in nature as the self-configuration concept in SON structure. With the addition of the memory, we achieve fast and effective configurations.
- We model the concept of T-cell in nature as the self-healing. Together with the self-optimization we achieved a successful control over self-configuration.
- We model the concept of thymus in nature as the concept of self-optimization. With this matching we achieved flexibility in organization policy.

2.2 Literature Research

The literature review presents a detailed study on the concept of bio-inspired networks and immune system. Through the literature research, we found many studies that present mappings from biological concepts.

In [7], the authors proposes an immune system inspired object tracking algorithm. In a sensor network, sensor device's duty is collecting knowledge about a specific attribute for a limited time period. This time period is usually determined by the power consumption of the devices as they have limited batteries. Based on this fact, the energy efficiency in a sensor network is one of the most important objectives. To maintain energy efficiency, usually the communication between sensor nodes is optimized. In many studies, a centralized controller performs this optimization. However, [7] argues that such a centralized structure will cause bottlenecks in the data flow which will eventually decrease both energy efficiency and performance. Instead of a centralized structure, they offer a distributed optimization framework that is mapped from the immune system in nature. They are defining the objects that need to be tracked using the antigen concept in immune system. Naturally, the sensor nodes are defined based on the B-cell (antibody) concept in immune system. Using this two

main mappings, they propose an immune inspired track observation algorithm that decreases the unnecessarily working devices and unnecessary communications. In [8], the authors proposes an opportunistic spectrum access framework that is inspired from the immune system. The opportunistic spectrum access framework tries to identify the unused frequency regions by the licensed user. In this study, the authors map the B-cell concepts as secondary users and inspiring from the antigen concept in the immune system, they define the spectrum opportunities. By this way, they present an error-tolerant, adaptive and efficient spectrum access policy. In [9], immune system concepts are used to detect the possible threats in computer networks. As the immune system is capable of detecting possible antigens and remembering them, it is argued that it will be efficient for network security. It is also stated that the immune system mapping is valid for dynamically changing network structures where the definition of threats changes over time. The authors propose two different mechanisms to detect the non-self cases, i.e. positive characterization (PC) and negative characterization (NC). In PC, the self-states are determined and the remaining states are accepted as non-self states. In NC, the non-self-states are determined and the remaining states are accepted as self-states.

In [10], a bio inspired cooperation framework is proposed for mobile devices. The authors investigate the biological systems, i.e. behaviors of vampire bats and monkeys, and based on their observations, they investigated the cooperative and non-cooperative frameworks. The behaviors of vampire bats and monkeys are the main inspiration sources of this study. The blood sharing framework among the bats presents the two important attribute in the cooperation within the same group, namely, reciprocal behavior and detection of cheaters. From the behaviors of the monkeys, they observe the other two concepts of cooperation, the domination of markets by the behavioral economics and the tolerance to the pay-off delay. Using these observations they propose a cooperation framework containing two kind of users, cooperative ones and non-cooperative ones. They investigate the different combinations of these device types within a network and concluded that the pure cooperative and pure non-cooperative networks are better than hybrid networks.

[11] proposes an optimization framework for the servers energy consumption. They used the antigen structure in immune system and defined two different antigens, i.e.

self-antigens and non-self-antigens. The self-antigens are defined as the optimal energy consumptions whereas the non-optimal energy dissipations are modeled as non-self-antigens. During the initial state, they observed the server and gathered information about the possible states of the server and created an immune memory knowledge base. After this step, when a new state is encountered first they search this state in the knowledge base and decide whether it is a self-antigen or not. If it is a non-optimal state (non-self-antigen) then they use actions to optimize the servers energy consumption.

In [12], the authors points out the importance and challenge of energy optimization in eNBs in LTE cellular systems. Pointing out the challenge of traffic flow determination, the authors argue that a valid solution to this energy consumption can only be founded with a complete knowledge about the traffic. These traffic aware eNBs can optimize their energy consumption with a successful on/off-switching schedule. To gain this awareness, they propose that each eNB should sample its own traffic with a high frequency. They argue that increasing the independent traffic awareness can increase the overall joint traffic uncertainty. They also propose a stochastic game theoretic algorithm to increase the traffic awareness.

[13] presents another security application of immune system mapping. The author proposes a self-moderation framework for wireless discussion forums. Inspiring from the immune system concepts, an auto-management structure is designed. Thinking the discussion from as a biological organism, they defined the immune cells as the moderators and the misbehaving agents as the inflected cells. By redefining the producing antigen process as banning agents, they constructed their immune inspired system. They modeled the network forum as a network of agents that are using a PKI encryption algorithm. Using these basic mappings, they build a self-managing adaptive modulator structure that can detect the misbehaviors automatically and can perform actions quickly.

In [14], a solution to the energy efficiency problem is covered and a dynamic cell-expansion framework is proposed to increase the energy efficiency. It this study, it is stated that the sleep mode can only decrease a small portion of the overall energy consumption within the base station. Putting all the devices in sleep mode can solve the energy problem but it decreases the throughput. It is also argued that only a

combination of sleep mode and cell-expansion techniques can produce a more realistic framework. Based on this argument, an integrated combination of different concepts, i.e. cell-expansion, frequency reuse, cooperative working among base stations, is presented in [14]. They argue that to reduce the energy dissipation two separate paths can be followed. First of all, the transmission power should be decreased and the transmit energy should be saved. The second path is the turning off the base stations and compensating for the coverage loss through cell expansion. To manage this second path, a cooperation framework is applied.

During our literature research, we also paid a specific attention to the LTE-A system and its attributes. In [15], an overview and the presentation of different attributes in LTE-A systems are presented. The authors explain the specifications of the LTE-A system starting from physical overview. Then they present the weaknesses of LTE Release 8 and then explain the newer attributes that LTE-A proposes like carrier aggregation or CoMP transmission and reception. In heterogeneous networks section they also investigated the relay nodes and finally they evaluated the LTE-A performance in terms of downlink and uplink speeds. A more specific research is presented in [16], where the carrier aggregation concept is investigated more detailed. In this study, first, the concept of carrier aggregation and the increase in capacity demand that triggered the LTE-A researches is stated. Then using different deployment scenarios, the design of LTE-A systems is presented. The design process is researched in two topics, higher layer necessities and physical layer expectations. [17] provides a power dissipation analysis in the heterogeneous networks that contains femtocells. In this study, the authors uses the system bandwidth to measure the QoS. They also present an investigation of the relation between system power consumption and average transmission bandwidth. We also applied the proposed mobile terminal energy formula in our study while calculating the transmission energy.

Mapping the immune system concepts brought out the necessity to find a base study that covers the mechanism of how the immune system works. We used [18] to construct our design. In [18], a simulation framework for the immune system is presented. The authors first gives a detailed definition of the immune system and the connection between these concepts. Then they produce *IMMSIM* that simulates the B-cells, T-cells, APCs, antibodies, antigens and antibody-antigen complexes. Their proposed

simulation tool, *IMMSIM*, simulates the immune responds. In our study, the immune system structure that is presented in [18] is accepted as a base for the immune system. In [19], the authors first presents an overview on the concept of bio-inspiration and listed the most favorable reasons to use bio-inspired systems like, simplicity, durability and stability. They investigated the most favorable three of the biological systems, i.e. ant colony, immune system and cellular signaling, and provided an overview of design and implementation of attributes from these systems. [20] is an overview on the concept of energy efficiency and summarizes the applied studies on energy efficiency on LTE systems. The author separately investigates the energy consumption degradation studies on main base station equipment, cooling systems and 3GPP. It finally summarizes the applied advantages on the energy efficiency.

[21] presents a strong discussion about the biologically inspired internet architecture deployment. The authors argue that the increase in service demand and the diversity of presented services brought out the need of a new architectural and protocol design for the next generation internet. They argue that the biological systems are especially efficient for the design of next generation internet framework as biological systems are composed of multitude of protocols and they presents a hierarchical ecosystem structure that allows various systems to coexist. The authors emphasize that the existing structures contains specific and single biological systems to solve a specific problem. However, they propose the usage of the combination of different biological systems. As the structure of the future internet, they propose a fully integrated system of systems framework. They investigate the challenges of virtualization and adaptive resource management, energy efficiency, flexible and evolvable infrastructure and service-oriented provisioning. They researched a large variety of biological schemes, i.e. nervous system, lateral line, quorum sensing and predator-prey interactions. Two possible integrations of biological systems and network structures are presented, i.e. services integration, control and optimization (SILO) and information transfer data services (ITDS).

[22], the sensor network's lifetime challenge is investigated. The main argument is to increase the network's lifetime by activating the minimum number of sensor nodes that can provide a sufficient performance and scheduling the sensor devices on/off states. It is also proposed that arrangements in the report frequencies of sensor nodes

are necessary to achieve the minimum energy consumption. In this study a immune system inspired node selection algorithm is applied to determine the minimum number of sensor nodes. The proposed framework regulates the event reporting frequency and maintains the energy efficiency. The authors models the B-cell, antibody, T-cell, pathogen and antigen concepts as sensor nodes, sensor data, rate control parameter, event source and estimation distortion, respectively. Each sensor node sends its encoded information to sink node. The excitation of the sensor nodes is connected to the three main stimulations, i.e. affinity between the sensor node and event source, affinity between sensor node and uncorrelated neighbor nodes and finally affinity between sensor node and correlated neighbor nodes. The activation of the B-cell is determined with the summation of these three connections value.

2.3 Immune-Inspired Model

The self-organizing network management frameworks are proposed to automatically follow the changes in the dynamically changing network and maintain energy efficiency. However, in dense network structures, due to the capacity limit and energy consumption bound, the admission of some user requests need to be rejected. However, this "smart" rejection can be a challenging issue as the acceptance policy causes more complex structures. The memory addition increases the response speed and also can propose more efficient solution to the encountered problems. Anomalies and changes in a dense network topology, e.g. city centers etc., should be followed and the network topology should be changed according to some policies. As previously stated, SON is a solution but many proposed frameworks are complex and inefficient. Complex systems cause higher energy consumption and increases latency. Due to this reason, more basic memory control mechanism is needed. The main challenge in memory management concept is the data handling. As presented in [23], the type of data to be stored, the location of storage, the data integrity, effects of time on data and the data changing (both in terms of frequency and methodology) are open points in data handling. Immune system presents a simple way to handle the data that helps the immune cells to remember the previously encountered dangers.

We believe that mapping immune system concepts into SON framework can solve the existing problems. Apart from its simple memory management capability, immune

system presents a simple yet robust way to control the network. By its nature, it presents auto-memorization and auto-configuration concepts, which is essential to increase the performance in terms of throughput. The capability to detect possible threats is one of the most characteristic and important attribute of the immune system. By this way it achieves an early detection mechanism for the future dangers. As a summary, the self-organizing network management has to guarantee specific network parameters like resource management and QoS requirements. Besides adapting the network topology to increase the capacity, power consumption and planning is also crucial. In order to fulfill these objectives, we are proposing an immune inspired SON structure whereas the problematic high-energy consumptions of the base stations are mapped from the antigen concept in nature.

2.3.1 Immune system in nature

In human body, the immune system has a layered structure that presents protection in each layer. From this structure, we are mapping the cellular level defense of the immune system. This autonomous defense mechanism is evolved for the antigen structures that can pass through the rest of the layers of immune system and get into the living tissue. These antigens are the unknown and possibly hazardous proteins that do not usually exist in human body. These dangerous proteins, antigens, should be identified and destroyed before they actually harm the tissue. However, the main challenge is the successfully discovering the antigens. More specifically, distinguishing these proteins from the body proteins. As antigens are composite of amino acids, they have a vast different shape and structure that effects their chemical and behavioral specifications. This huge variety of kind makes it harder to detect every kind of antigens before they cause any harm. Human immune system contains B-cell and antibody structures to recognize and destroy antigens. B-cells are much like the “officer” cells in the body that are responsible for destruction of antigens whereas the antibodies are the “intelligent agents” of the body that are used to detect the antigens. Antibodies are created by a special kind of B-cells, depending on the previously encountered antigens. They consist of amino acids and they are capable of connecting to the antigens. They are completely matched to the antigen structure. When a previously destroyed antigen gets into the body again, these antibodies stick

to their surface. By this way antibodies make the antigens more recognizable and let the B-cells to connect them.

B-cells have protein extensions over their membrane structure. After the antibodies surround an antigen, a cellular level connection is created between B-cell and the antigen through the membrane extensions of the B-cell and the antibodies. Then B-cell pulls this antigen into the cell and surrounds the cell, B-cell assimilates the antigen structure. The assimilation process destroys some of the molecular connections between amino acids and by this way the antigen is destroyed. When the assimilation is over, the Major Histocompatibility Complex (MHC) molecules are produced using the divided amino acids during the assimilation phase. These MHC molecules are antigen specific and help B-cells to recognize the similar antigens much easier and quicker in the future. The MHC molecules stick to the surface of the B-cell. After this process, the B-cells need to divide to spread the knowledge of this antigen. However, the B-cells cannot divide directly after the destruction of the antigen. Instead they need a chemical signal from the T-cells in the body. Like B-cells, T-cells have extensions on their membrane structures. When a T-cell gets mature in thymus, it gets tested with all the body proteins in the thymus. If it makes any connection to any of these proteins, it is killed as this connection states that T-cells can trigger an autoimmune disease. If it does not create any connection then it is activated and spreads to the body. T-cells that are spread to the body contain knowledge of antigen structures and they need to evaluate the action of B-cell by connecting or not connecting to it. Making a connection to the MHC molecules on the B-cell states that B-cell actually destroys an antigen so a chemical signal is passed to the B-cell and allow it to divide. However, if it cannot make a connection, this states that B-cell is actually destroyed a body protein so its division must be prevented. By controlling the B-cells with thymus controlled T-cell structures, body protects itself from autoimmune disease.

2.3.2 Proposed biological scheme

In this study, the self-configuration, the self-optimization and the self-healing concepts in SON are defined using the three concepts in cellular level immune system, namely B-cell, T-cell and Thymus, respectively. The B-cells' attributes like auto-memorization, autonomous antigen detection and autonomous action selection

mechanisms are implemented to the immune inspired self-configuration structure. However, like in immune system, the autonomously performed actions may not be sufficient for the active network management policy. Due to this, the self-optimization structure is redefined using the specific attributes obtained from T-cell structure in immune system. More specifically, the activation process of B-cell's actions is mapped to the self-optimization framework. Finally, the network management objective controller is implemented in the self-healing mechanism so the changes in the network topology management objectives can be spread to the self-configuration and self-optimization blocks without destroying the other possible topology decisions.

Table 2.1: Power consumption model.

Immune System Concepts	SON Equivalents
Antigen	High Energy Consumption of SBS_i (ζ_i)
B-cell	Self-Configuration
T-cell	Self-Healing
Thymus	Self-Optimization

The success of the proposed Immune Inspired green Self-Organizing Network ($I^2 - gSON$) topology management framework highly depends on the success of the mapped definition of the antigen concept in immune systems. In this study, an antigen inspired structure is reconstructed to state the over-energy consuming small base stations. In Figure 2.1, the general structure of the proposed model is presented. During this study, we only cover the networks containing two types of base stations, i.e. Small Cell Base Stations (SCBS) and Main Base Stations (MBS). In the accepted cell structures, there could be multiple SCBSs whose duty is only handling the user communications whereas there only exist one MBS whose duties covers both handling the users and optimizing the network topology to produce maximum acceptance rate while maintaining the energy objectives of the network. The proposed self-configuration framework is applied to the MBS. The mapped concepts of immune system and their equivalents in our study are presented in Table 2.1.

2.3.2.1 High energy consumption concept(Antigen inspired):

As in the immune system, the most important attribute of the SON framework is the separation of states. In nature a molecular structure can be marked as one of two possible labels, i.e. self-molecule or non-self-molecule. The antigens are the molecules that are labeled as non-self-molecules. In our study, as we are trying to detect problematic states in terms of energy efficiency, the consumed energy in the base station is the main concern. As previously stated, the state of a small cell base station (SCBS) is determined from the number and the distribution of the users which effects the average power consumption of the SCBS to serve a user. So the average power consumption is used to measure the state of the SCBSs. As shown in Figure 2.1, we are labeling the states of each SCBS as self-state or non-self-state. To determine the state of a SCBS, we used an estimator of the state, $\zeta_i(t)$, as presented in (2.1).

$$\zeta_i(t) = \frac{P_{tr,i}(t)}{N_i(t)} \tag{2.1}$$

where $P_i(t)$ is the total dissipated power of the ith SCBS during the transmission and $N_i(t)$ is the number of users of the ith SCBS. As can be seen from this definition, the estimator shows the average dissipated transmission power that is consumed by the ith SCBS to support a single user at time t. $P_i(t)$ is different for each SCBS and it can be measured by using the minimum useful signal power and the distance between user and SCBS. Based on this definition, the consumed power for a single device is calculated by (2.2) .

$$P_{tr,i} = p \times d^{\alpha} \tag{2.2}$$

where p is the minimum useful signal power, d is the distance between user and the SCBS and α is the propagation constant. As the total transmission power dissipation is needed to calculate the estimator, (2.2) has to be generalized as (2.3) which presents the summation of single user power dissipations.

$$P_i(t) = \Sigma_{i=1}^{N} p \times (||L_{SCBS} - L_i||)^{\alpha} \tag{2.3}$$

$$||L_1 - L_2|| = \sqrt{((L_1)_x - (L_2)_x)^2 + ((L_1)_x - (L_2)_y)^2} \tag{2.4}$$

where $(L)_x$ represents the x location of ith device and $(L)_y$ represents the y location of the ith device. By importing (2.3) to (2.1), we get (2.5).

$$\zeta_i(t) = \frac{\Sigma_{i=1}^{N} p \times (||L_{SCBS} - L_i||)^{\alpha}}{N_i(t)}, \ \ \forall i \ \varepsilon \ N \tag{2.5}$$

where $L_{(I,k)}$ represents the kth user of the ith SCBS. In orderto present an understanding of the estimator state, the average user count, $N_{average}$, can be used instead of $N(t)$.

$$N_{average} = \lambda \times T_{average} \tag{2.6}$$

where λ is the arrival rate and $T_{average}$ is the average waiting time. By combining (2.5) and (2.6), (2.7) can be reached.

$$\zeta_i(t) = \frac{\Sigma_{i=1}^{N} p \times (||L_{SCBS} - L_i||)^{\alpha}}{\lambda \times T_{average}}, \ \ \forall i \ \varepsilon \ N \tag{2.7}$$

As can be seen in (2.7), the state of the SCBS varies with the arrival rate of the users to the cell, their average waiting time in the cell and their distances to the SCBS. The state labeling process is performed by comparing the estimator with a static threshold, δ_T. As shown in Figure 2.1, the state of the BS used as a heuristic in the determination of the non-selfness. If the state of the BS doesn't exceed δ_T threshold value then the base station's state is accepted as self-state. However if it exceeds δ_T, then BS is in a non-self-state and in this case $I^2 - gSON$ framework tries to optimize BS state by reconfiguration.

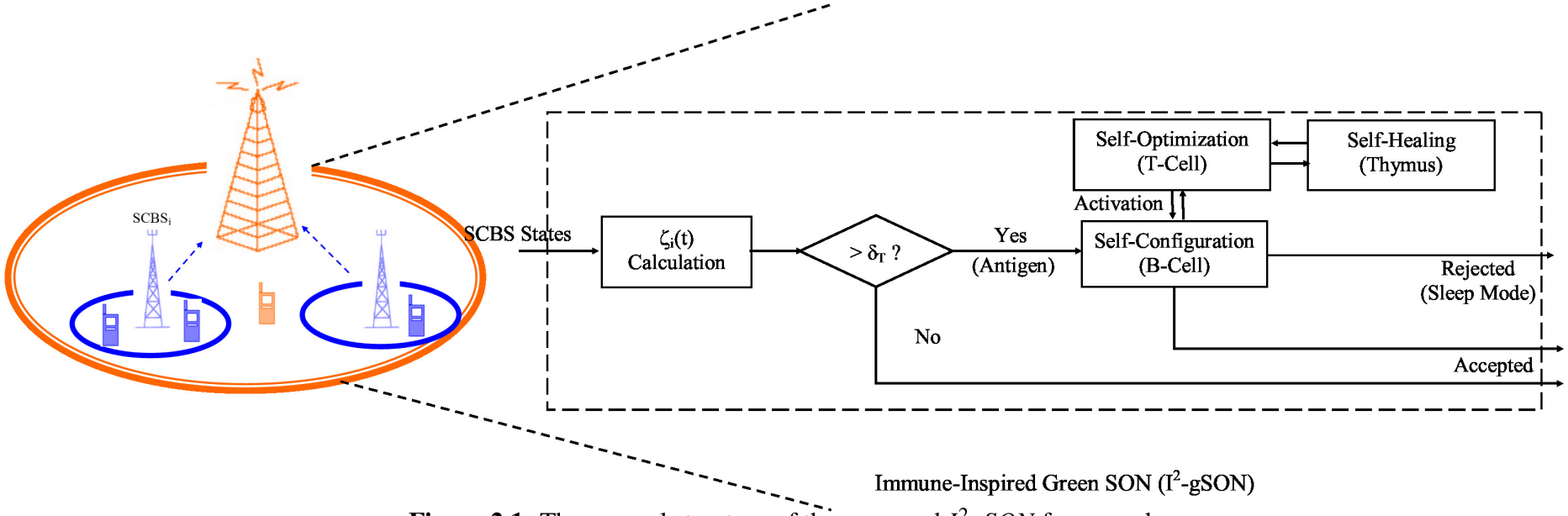


Figure 2.1: The general structure of the proposed I^2gSON framework.

2.3.2.2 Self-configuration concept (B-cell inspired):

The foundation of an antigen, a SCBS in the non-self-state, shows a leakage in the energy management. To cover this error, the self-configuration block is activated. Even though previously explained three variables (λ, $T_{average}$, $d_{(i,j)}$) change the state of a SCBS, rapid changes in λ and $T_{average}$ terms are not very likely. Due to this reason, the state change of a SCBS is highly because of the location of a user. To increase the energy efficiency, the self-configuration block can perform three actions, namely *user switching*, *coverage area changing* and *sleep mode*.

As stated earlier, a base station can enter a non-self-state due to the distance of the user or heterogeneity of propagation constant. If the distance of the lastly accepted user causes a non-self-state, the most optimal action is offloading this user from this base station and move it to another base station. Most of the cases, this action will decrease the estimator value and move it into a self-state. However, there could be the case in which the reason of the non-self-state is not the distance of the user but the heterogeneity of propagation constant. In such a case, the user's switching is not an optimal solution as it only puts another base station into non-self-state. For such cases, the second action is the coverage area change. This action decreases the transmission power of the BS and also makes the users at the edge of coverage region border change their connection. This action is more aggressive solution than user switching action as it can affect many unproblematic users and may also cause the fall of service quality.

If both of the actions do not manage to change the state of the BS, then the third and the most aggressive action is used, the sleep mode. In this case, the base station puts the lastly accepted user into sleep mode, and by this action, it undoes the previous state change and regains its self-state. However, as stated earlier this action is the most aggressive action and the selection of it has to be the last case. By using these three actions, the state of the base station is changed into the self-state. However, the selection of these three action is critical. The selection of the sleep mode action at the first place can be problematic even though it changes the state of the BS. In this study, we used a probabilistic approach in the action selection order. All three actions are selected with different probabilities, P_1, P_2 and P_3 where P_1 is the probability of selecting the user switching action, P_2 is the probability of coverage area change action

selection and P_3 is the probability of selecting sleep mode action. The summation of these three probabilities is equal to 1. The values of these probabilities are crucial because they cause a tradeoff between the most energy efficient configuration and the best user service. To clarify this tradeoff, assume that $P_3 = 1$ and $P_1 = P_2 = 0$. In this case, all the non-self-state changes are prevented however the presented service will be worst as most of the users are sent to the sleep mode.

After choosing an action, a connection between the action and the base station is made. This connection is mapped from the MHC molecules in the nature and it is used to find the optimal solution faster in the future. For example, the only efficient action for a BS can be the sleep mode action. However, due to the probabilistic approach the change of the selection of this action is very low. Because of this, the time to find the efficient action can be very long. This connection between BS and the active solution shows the easiest way to change the state of the BS. Even though this connection is important, the activation time of this connection can be problematic. If the connection is activated right after the selection without any optimality check, then the memory will be full of inefficient actions defined for BS. Instead of activating this connection quickly, it is kept in temporary memory. After the self-optimization and self-healing, if the action is actually efficient then it is activated and passed to the long-term memory. Otherwise it is deleted and a new action is selected. While selecting a new action, the previous action is deleted from the action space so it is guaranteed that the new action will be different. By this way, stacking in a loop of inefficient action is prevented. If there exist a connection between the BS in non-self-state and an action, then this action is selected. Even though the action is decided because of a connection, its optimality is checked again, and if it is found inefficient, then, again, this connection is deleted and a new selection is made.

2.3.2.3 Self-optimization concept (T-cell inspired):

The B-cell changes the network topology to maintain the energy efficiency, however, the probabilistic structure of the action selection process may result in the non-optimal solution selection. Due to this reason the observed problematic network topology and the applied action couple should be checked whether they are optimal or not. The proposed self-optimization module in I^2gSON performs this optimality selection process. The T-cell concept in immune system is mapped to design self-optimization

structure. In nature, the performed action is evaluated by the T-cell and based on the accuracy of the B-cell's assimilation process, T-cells controls the division of B-cells. By this control mechanism, B-cells division is prevented if it destroys a body protein and autoimmune disease is prevented. Like the T-cells in immune system, the self-optimization bloc in the proposed framework controls the activation process. As stated earlier, if the inefficient actions is defined and activated to BSs, the framework may never reach an efficient action and because of this, the objectives of QoS and energy efficiency may never be achieved.

Self-optimization bloc receives the network objectives from the self-healing block. In this study, we only cover the energy efficiency policy. More specifically, the network tries to optimize the energy efficiency even if it sometimes causes low acceptance rate. Because of this single policy structure, the network management framework tries to decrease the energy consumption by choosing one of the previously explained actions. When the self-configuration block performs an action it produces a couple, i.e. the observed problem and the performed action, and transfers this couple to the self-optimization block. In self-optimization block, this received couple is evaluated according to its two attributes, the necessity of the performed action and the observed efficiency. As there exist three possible actions, their possible application sequence is determined by how aggressive they are. It was stated that the sleep mode action is the most aggressive one whereas the coverage area degradation is the least aggressive action. T-cell investigates the sequence number of the applied action and decides whether it is effective or not. By definition, it is not acceptable to choose a more aggressive action before selecting a least aggressive action. If the self-configuration's action decision violates this rule then the received problem-action couple is not activated. Otherwise the self-optimization bloc rechecks the antigen value of the SCBS. If it is still labeled as an antigen then again the couple is not activated. However, for this case, the network has the change to choose a more aggressive action. If the problem-action couple passes all these objectives than it is activated and stored to the memory.

2.3.2.4 Self-healing concept (Thymus inspired):

T-cell inspired self-optimization block evaluates the applied action of the B-cell inspired self-configuration block. This evaluation process needs some objectives that can be determined according to the changing policy of the network. The network management may choose an energy efficient policy or a performance-oriented policy to perform. Such changes in the network management policy changes the problem definition, more specifically, the antigen determination process. For a performance-oriented policy, antigen determination threshold, $\delta_{T_{performance}}$, is quite higher then the energy efficient policy threshold, $\delta_{T_{EE}}$. In this study, for simplicity, only the energy efficient policy selection is performed. The self-healing block only transmits the objectives of the energy efficient policy.

The self-healing module is inspired from the thymus structure of the human body. Thymus tests the T-cells with each body protein during their maturing process. It kills the cells that connects to the any of the body proteins and by this way only allows the existence of T-cells that are passive toward body proteins. This defined process is the equivalent process of the policy objective determination process in the self-healing block. The body proteins in thymus can be modeled as the objectives of the network policy. In this study we are modeling a constant network management structure, with static self-optimization and self-healing structures. However, the proposed self-healing framework can support the dynamically changing self-optimization structures that are controlled by the self-healing structure. The self-healing block is capable of determination of the network policies. Like self-configuration block, self-optimization block can decide on the objectives from a previously defined objective space and the self-healing bloc can determine the optimality of the accepted objectives to the network policy. Unacceptable objectives can be rejected. By this way, the network is capable of dynamically choosing the optimal objectives for the given network structure and the network policy. However, as stated earlier, we are using static self-healing block in this study. It only returns the optimal energy efficiency policy to the self-optimization block. The self-optimization bloc uses a static threshold value to determine the problematic states, $\delta_T = \delta_{T_{EE}}$.

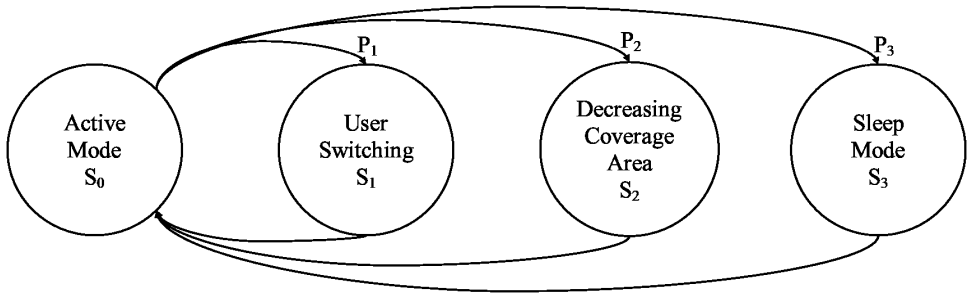


Figure 2.2: Markov model of possible BS actions

2.3.2.5 Markov model of possible SCBS actions:

As stated in Section 2, three possible actions are defined to change the state of the base station. These are user switching action, coverage area decrease action and finally sleep mode action. We also stated that each action is going to be selected with different probabilities, P_1, P_2 or P_3. The Markov chain state diagram is presented in Figure 2.2. As can be seen in Figure 2.2, a small cell base station can exist in four main state with four state probabilities. First one is active mode. If there exist no active actions defined for a SCBS then it is in active mode state. A SCBS can be in this state with probability S_0. This state also shows that this BS has never be in a non-self-state. Other three states are the possible active actions that can be defined for a BS. The SCBS can be in one of these states with state probabilities S_1, S_2 and S_3. If the base station is in an active action state, it will turn to active mode state if the defined action is no longer an efficient action for this BS. The probability of existing in a state is S_0 then existing in any other state is,

$$S_1 \times (1 - P_1) = P_1 \times S_0 \tag{2.8}$$

$$S_2 \times (1 - P_2) = P_2 \times S_0 \tag{2.9}$$

$$S_3 \times (1 - P_3) = P_3 \times S_0 \tag{2.10}$$

$$S_i = \frac{S_0 \times P_i}{(1 - P_i)} \tag{2.11}$$

$$S_0 + S_1 + S_2 + S_3 = 1 \tag{2.12}$$

Using (2.11) and (2.12), we derivate the general state probability of S_0, (2.13).

$$S_0 = (1 + \frac{P_1}{1 - P_1} + \frac{P_2}{1 - P_2} + \frac{P_3}{1 - P_3})^{-1} \tag{2.13}$$

As P_i values are static, we can calculate the possibilities of existing in each state. For $P_1 = 0.5$, $P_2 = 0.4$ $P_3 = 0.1$, we find $S_0 = 0.36$, $S_1 = 0.36$, $S_2 = 0.24$, $S_3 = 0.04$. These

probabilities also shows that in steady state 36% of the base stations will be in active mode with no constant active action while 64% of the base stations have an efficient action which does not need to change.

2.4 Simulations

The main objectives of the proposed immune inspired framework can be itemized as;

- Increasing the energy efficiency
- Decreasing the fluctuations in the energy consumption
- Increasing the number of accepted user requests
- Maintaining a more stable network management framework

The success of the proposed framework is measured in terms of acceptance ration and the energy efficiency. We compared the proposed immune inspired network topology management framework with the existing sleep mode self-organizing network topology management framework ($SM - SON$). In $SM - SON$ framework, the high energy consumption is decreased by putting the problematic user requests into sleep mode. The defined coverage area change action in the optimization process may cause coverage holes where the users cannot access to the system. Such an error may increase the energy efficiency but it decreases the network performance in terms of user satisfaction. Due to that, as in [24], we leave readable broadcast channels over the whole network that is maintained by the main base station. All the users that are not connected to a SCBS is connected to the MBS. The applied network parameters are presented in Table 2.2.

Table 2.2: Simulation Parameters

Number of MBSs	1
Number of SCBSs	10
Self-state threshold	3.5 mW/User
P_1	0.5
P_2	0.4
P_3	0.1

While we were evaluating the stability of the proposed framework we changed the P_i parameter and observed the change of the acceptance ratio. During the simulations, at each time unit, a random request comes to a SCBS and the power consumption of the network is increased. In simulations the main assumption is that only one request can come in a single time unit.

2.4.1 Performance evaluation on energy consumption

Energy efficiency is one of the key concepts in this study. The total energy consumption of the network is calculated by summing energy consumption of each SCBS and the main base station. The energy efficiency performance of proposed I^2gSON framework is compared to the $SM-SON$ framework. In Figure 2.3, the total transmission power change over time is presented for the steady network case (the transient state results are not presented). From the presented result in Figure

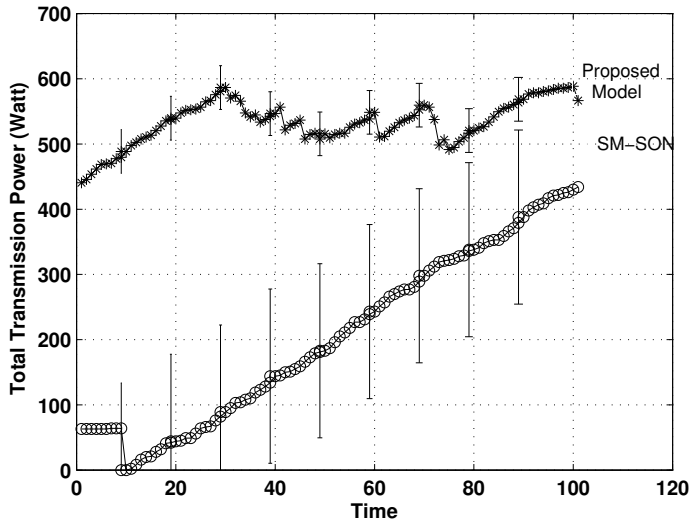


Figure 2.3: Energy consumption change

2.3, two important argument can be extracted. First of all, the proposed framework presents higher energy consumption. Note that for each SON framework, we defined the same non-self state threshold, which states that both of the frameworks are encountering their first non-self state at the same time. However, as the I^2-gSON presents an improved configuration model, it increases the number of users, which eventually leads a higher total power consumption. Nevertheless, this high power consumption does not mean low energy efficient, as an inefficient energy state would trigger the configuration and eventually leads putting the problematic users into sleep

mode. Secondly, the fluctuations in energy consumption are a long-term problem for network management. For the proposed framework, the maximum amplitude of energy consumption is around 50 mW whereas the $SM-SON$ framework presents an unstable energy consumption trend with fluctuation amplitude of 200 mW. This proves that the proposed framework is using its capacity more efficiently as the energy consumption is highly connected to bandwidth. It can also be argued that the peak to peak amplitude of the energy level is lower in I^2-gSON. It can also be seen that after 10th minute, the energy consumption of the $SM-SON$ increases linearly. The energy oscillation of the I^2-gSON shows that the network topology is capable of maintaining the energy consumption around 550 W. The linear increase in $SM-SON$ can be explained by the randomly created user locations and this upper bound. At the 10th hour, the $SM-SON$ returns the initial state with no active users. After that with a good user distribution and no non-self-state detection, the energy of the network increases linearly. However, as the transient state of the network is not presented in the figure, this increase in $SM-SON$ shows the instability of the network.

2.4.2 Performance evaluation on acceptance rate

Device throughput is the main considered Quality of Service (QoS) expectation of this work. The QoS requirement is measured by the acceptance ratio in this study. In previous part, we observed that the proposed framework ensures a more efficient network topology in terms of energy consumption. However, to state that the proposed framework is superior than $SM-SON$ in terms of energy efficiency and throughput, we have to guarantee that the proposed framework does not demand a sacrifice in QoS. The number of accepted requests measures the acceptance rate over all the received requests. In Figure 2.4, the number of accepted requests is showed for both the $SM-SON$ and I^2-gSON. The results are divided for 10 SCBSs and there exists 50000 requests in total. Based on these results and the total number of requests, we calculated the acceptance and rejection rates for the frameworks. The observed results are presented in Figure 2.5. The simulation results measures a 26% of increase in the acceptance rate. This increase proves that the proposed framework increases both energy efficiency and QoS. This high increase in acceptance rate is highly because of the decrease in the number of devices that are putted into sleep mode due to the

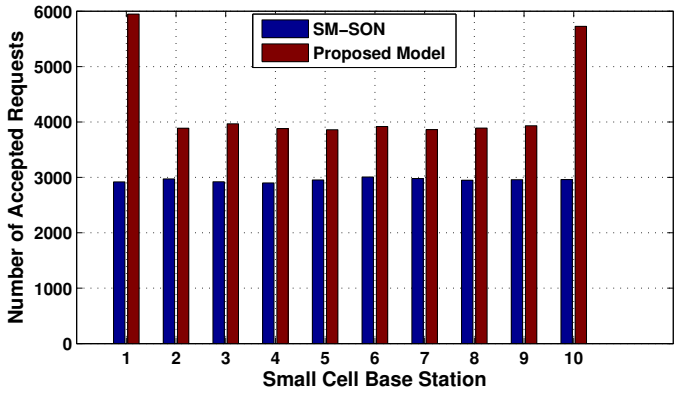


Figure 2.4: Number of accepted requests

inefficient management. $SM-SON$ is a primitive topology management framework that changes the user communication schedule according to the energy consumption. This states that $SM-SON$ is not efficient for dense and dynamically changing networks. However, I^2-gSON is an improved topology management framework that changes the network topology and configures the base stations according to the network demands. It is more complex then $SM-SON$, however, it is more suitable for dense city networks.

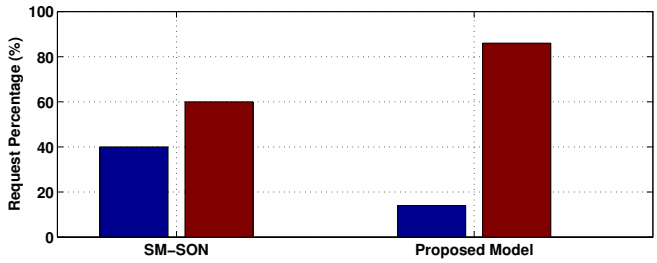


Figure 2.5: Acceptance and rejection rates

2.4.3 Flexibility analysis of proposed framework

In previous parts, we proved that the proposed I^2gSON framework is effective for dense and dynamically changing networks. However, it is an obvious fact that it is more complex than $SM-SON$, which makes I^2gSON more sensitive to possible changes and mistakes in the system. The stability of the proposed framework in terms of system architecture should be investigated in order to argue that it could be applicable. There exist a vast number of system parameters that needs to be observed to determine the stability of the framework. However, in this study we observed the P_i parameters on acceptance rate. More specifically, the effect of P_3, probability of

sleep mode action selection, on acceptance rate is investigated. The obtained results are presented in Figure 2.6.

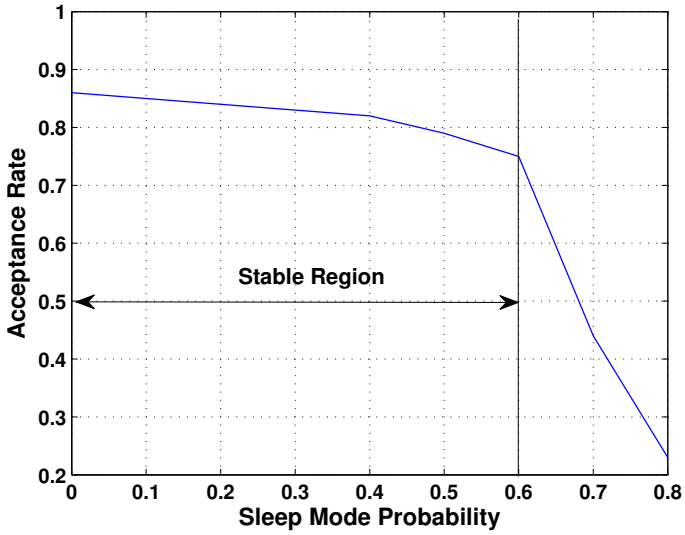


Figure 2.6: Acceptance rate change with sleep mode probability

It was expected that the increase in P_3 will cause a decrease in the acceptance rate as the network configuration framework mostly becomes a user scheduling framework. To evaluate the stable region, we accepted that the topology management framework is stable until the acceptance rate decreases 10%. In Figure 2.6, the stable region is showed. The proposed immune inspired system is stable until $P_3 = 0.6$, which also indicates that $P_1 = 0.2$ and $P_2 = 0.2$. After this borderline, the system rapidly becomes unstable and acceptance rate decreases quickly. At $P_3 = 0.8$ the acceptance rate is at the level of 0.25 which is smaller than the $SM - SON$ structure. This is mostly because of the active policy of the network management framework. During the optimization process, the selection of sleep mode action in the first place is disabled. Due to this reason, the proposed framework is worse than $SM - SON$. This result shows that for a large range the proposed framework keeps its high success rate and energy efficiency. This is mostly because of the T-cell inspired self-optimization structure, which prevents the selection of sleep mode action at first. By this way, the network tries to accept the user request and uses the scheduling action at the last resort.

3. SELF-ORGANIZED THINGS

Through the last decade, while the technological capabilities of commercial electronic devices increases, they became cheaper. This economical and technological improvements have lead an enormous increase in the number of small electronic devices, which have communication capabilities. Consequently, the concept of Internet of Things, IoT, has emerged as a promising framework. At a higher level the IoT can be defined as establishing connections between electronic devices, things, i.e. varying from every kind of sensor to smart phones and even cars. The integration of IoT into the daily life, provides many advantages to many fields, e.g. planning, medicine or security. Many optimistic scenarios are presented about this advantages, like the one presented in [25]. According to this scenario, due to the communication between a business man′s alarm clock, coffee machine and car, a great morning planning can be executed. However, the realism of these scenarios is doubtful.

Behind the optimistic scenarios about IoT, there exist many challenges like the ones stated in [26–28], i.e. users security and privacy or routing technology or communicating different kind of devices or handling all these huge amount of data while keeping the energy consumption low. Even for scenario in [25], if there exist an interruption to the plan the whole easiness and efficiency will be lost. It is also indicated that the only way to gain complete knowledge and prevent interruptions is using more sensors. However, this increase of devices will cause an increase in raw knowledge and energy consumption.

The energy efficiency in IoT is one of the hottest topic nowadays because of both economical and environmental concerns [26], i.e. Capital Expenditures (CAPEX), Operational Expenditures (OPEX), lack of resources and the global warming. The service persistence, more generally durability, changes with the energy efficiency as for the most of the cases the main reason of device losses is based on the battery exhaustion. Secondly, self-management is also crucial for IoT concept [26]. As stated earlier, the number of devices that surrounds us is exponentially increasing and the IoT is becoming unmanageable. This unmanageability of IoT network is mostly

because of the lack of human force along with costs and complexity. A most rapid and possibly the most efficient solution is to define a self-organized framework for the IoT concept. These IoT devices are specific electronic circuits that are designed to perform some specific objectives. For example, a coffee machine prepares coffee and an air conditioner changes the quality of air. The specific attributes like “hot coffee” or “cold air” can be generalized as specific events of IoT devices. It is possible to define a specific action range for each of these devices where they can observe and detect these events. For a coffee machine this observation area is nearly equal to zero, which states that the event can only be observed within the device. Nevertheless, the range of an air cooler is larger than the coffee machine. All these observation ranges are called as coverage area in this study. For simplicity, we accept that all devices have the same coverage area. The technological trend presents the challenge of fully covered areas as being completely covered shows that this area is suitable for smart operations and planning. As the only way to expand coverage area is increasing the number of devices, a trade off between coverage area and energy efficiency appears. As the communication rate increases this trade off becomes more visible.

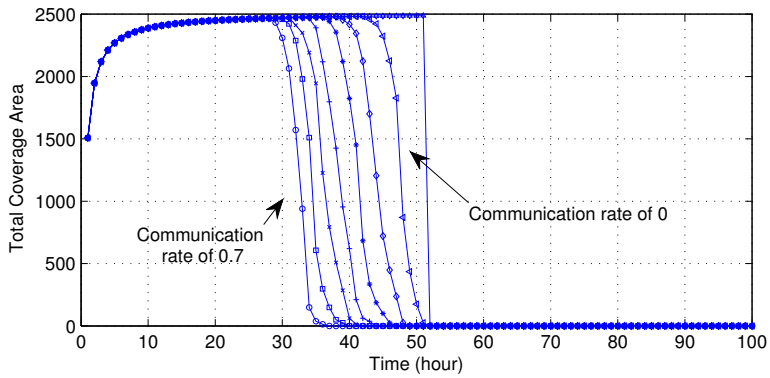


Figure 3.1: Coverage area changes for different request rates.

This trade off between energy and coverage area is presented in Figure 3.1. Here, a "communication rate" can also be defined as the dimensionless rate of active communication time over the total time interval. In this figure, the coverage area changes under different traffic requests are presented for a generic IoT model that does not use any scheduling or management improvements. Without energy optimization the maximum lifetime, that can only be achieved by 0 traffic rate, is 50 hour. In Figure 3.1, it can also be seen that increasing communication rate decreases the energy efficiency and also decreases the lifetime of devices. This inversely proportional

relationship between the energy consumption and network lifetime durability should be carefully addressed with a self-management perspective [4]. However, for many cases energy efficiency can only be achieved by the loss of coverage area.

3.1 Purpose

Even though many researches is going on, as stated in [28], IoT is still the "Wild West" of technology. The most crucial challenge in IoT is increasing the lifetime of IoT devices without a sacrifice of performance. Consequently, by considering all these aformentioned recent studies, and with the motivation of merging the self-management issues by optimizing the energy consumption with coverage area for IoTs, in this paper, we present a novel self-organized internet of things framework, named Self-Organized Things, SoT, by making the following contributions;

- By defining three main self-organizing concepts [2], i.e. self-configuration, self-optimization and self-healing, the human intervention is decreased. Thus self-management is achieved.
- In self-configuration of the proposed SoT, two parameters, i.e. conflict parameter, ξ_i and spatial correlation parameter I_k, are defined. Even though there exist some works that uses this kind of parameters separately, to the best of our knowledge there exist no work that integrates both of them. We are presenting a novel approach that integrates both of these parameters with self-organizing framework and by this way increasing the coverage rate in the network.
- In self-optimization, a spatial correlation parameter, I_k and conflict parameter, ξ_i, are calculated as decision parameters to reach an energy efficient topology.
- We develop a sleep mode optimization mechanism to minimize the unnecessary energy consumption and stabilize the battery lifetime.
- In self-healing, the device losses due to battery limitation are compensated and with the energy efficiency increase, gained by self-optimization, we are increasing the durability of the network.

3.2 Literature Research

In citeHulburt, the concept of Internet of Things is investigated. First the definition of the IoT devices, and their capabilities are presented. An introducing example about the businessman is presented in this paper. This special example, which we presented in the following chapter, presents the importance of scheduling in IoT networks. The reality of the IoT scenarios is investigated in terms of data handling, security, implementation, ownership, costs and privacy. [29] introduces the concept of intelligent self-organization for IoT. In this study, two challenges of IoT deployment, i.e. scalability and heterogeneity, are considered and proposed that self-organization can handle these challenges. In order to propose a self-organized structure, the authors inspired from the endocrine system in human body. They argue that four item should be expected from a self-organized IoT deployment which are decentralized structure, efficient collaboration, energy efficiency and intelligent service discovery. It is argued in the text that the empowering nodes with self-management and autonomic capabilities is challenging in heterogeneous IoT networks. To overcome this challenge, they used the endocrine system concepts while defining the self-organizing structure. Two possible states are defines for IoT devices, namely sleep and wake. Using the bio-inspired self-organization scheme they proposed a sleep control scheme.

[30] points out the discontinuous reception optimization problem and they proposed a three stage scheme and a packet scheduling method to handle this problem. They argue that there exist an uncertainty in the literature on how to tune the discontinuous reception and transmission parameters to gain the most energy efficient structure for the users. In their proposed scheme, during the wake up period, device checks the channel to see if there is any request from the base station. They also proposed a packet-scheduling scheme for the eNB. [31] investigates the applicability of the Wi-Fi while maintaining the IoT connections. This investigation is performed in terms of power consumption, interference and communication range. The authors state that usage ZigBee and other IEEE 802.15.4 protocols to maintain the connection of IoT devices should be reconsidered, as more energy efficient network structures are available with Wi-Fi. They consider three different scenarios for the IoT networks. In

each scenario, the accepted IoT device type is different. Using hourly triggers they investigated the power consumption of devices. It is argued that except for the large packet transmissions, the power consumption due to communication is negligible for Wi-Fi connected IoT devices.

In [32], it is argued that to maintain energy efficiency and decrease the carbon footprint without performance degradation, dynamically adjusted transmission powers and on/off switching amongst the unused parts of the base station is a promising way. Based on this argument, they propose that network scaling can be applied to decrease the energy consumption while maintaining performance. They propose five scaling down methods, i.e. carrier scaling down, site scaling down, sector scaling down, carrier-site joint scaling down and orthogonal site scaling down. They calculated the different scaling methods effects on energy consumption using the actual data obtained from a base station. Based on the simulation results, the optimal scaling action for suburban areas is the usage of both carrier scaling down and sector/site scaling down, simultaneously.

[33] surveys the different cooperation schemes in terms of their advantages and disadvantages. It is argued that such cooperation can be applied to increase the energy efficiency and spectrum efficiency. Depending on this argument, the authors researched the different cooperation schemes in relay systems and node cooperative systems. After this survey, two intra cell CoMP schemes are proposed and their efficiency in terms of spectral efficiency is investigated. In [34], the concept of internet of nano-things is investigated. It is argued that the nanodevices should not be constrained by the P2P communications. The authors claim that usage of embedded nano sensors will bring a new dimension to the IoT concept. The challenges in the nanonetworks are presented in this study. The inefficiency of the EM communication is the most important challenge in nanonetworks. The authors mention the concept of molecular communication to maintain the communication between different nanodevices. The additional challenges risen from the usage of molecular communication, i.e. system architecture or routing technology is also covered in this study. Finally they propose three different application areas for nanodevices, i.e. intra-body networks, disease control framework and environment control application.

[27] provides a general description of the IoT networks. Firstly, a short description of the IoT is presented, which can be stated as "providing artificial services by the connected daily devices with identifiable addresses". The author presents the four-layered structure of the IoT network. The mentioned challenges of the IoT network are non-uniformity, inconsistency, inaccuracy, discontinuities, incomprehensiveness and incompleteness. Addition to these challenges, the author argues that heterogeneity, data integrity and service adaptation are the problems that needs to be considered while handling the IoT challenges. [28] states that IoT is still a novel concept that has no solid borders and mainly using adhoc solutions. In this study, the difficulties of connecting devices in both physical world and digital world are explained. the authors draws attention to the challenge of connecting different devices that are using different technologies and services. Even though the connection is performed, handling the produced heavy traffic load is stated as another challenge. It is argued that intelligent energy management frameworks are necessary in IoT deployments as all the IoT devices are limited with batteries. [35] proposes a clustering protocol for wireless sensor nodes. By definition sensors have low computation capabilities, limited buffer size and their lifetimes are constrained by their battery life. Like IoT networks, in sensor networks, an energy efficient management is required to increase the system durability and eventually decrease the OPEX. It is argued that an energy efficient clustering algorithm can maintain network wide energy efficiency as it decreases the number of control signals. Based on this argument, in [35], a self-organized energy conscious clustering (SECC) algorithm proposed to group the sensors according to their energy and distance.

[36] argues that the determination of transmission reliability and energy efficiency in a multistage cooperative sensor network is challenging. They propose that the multistage cooperation is a promising concept for sensor applications as it decreases the transmission power to obtain a static outage probability. However, they also argue that with increasing number of cooperation stages, the energy efficiency of the cooperation will decrease significantly. Hence the authors present an analysis on the energy efficiency of multi stage cooperative networks in this study. They evaluated the performance of the network in terms of transmission reliability and energy dissipation cost. The effects of network size and cooperation stages on the

network performance are investigated in the numerical analysis part. In this evaluation, two network scenarios is applied, i.e. equidistant network topology and uniform relay distribution. The authors observed that equidistant topology network is more energy efficient than uniform relay distribution. Additionally, for equidistant topology network, the maximum energy efficiency is obtained with five cooperation stages for 30 relays.

[37] proposes a cellular automata based topology control framework for wireless sensor networks (WSN). In this study, a decentralized algorithm is proposed for the challenge of energy efficiency in WSN. Their objective is to find the optimal topology that contains the minimum number of active nodes and scheduling the on/off states of these devices, increasing the lifetime of the WSN. In this study, each individual device decides its state according to the states of its neighbors. At the initial state, they put all the battery-limited devices into on mode. At each time unit, each device decides its state in the next time step. The applied rule in this study is to be "on" state if there is less than two active neighbors and being in "off" state if there is greater or equal to two neighbor cells in on state. The on state of a device is the active state and the off state of the device is the power saving state. Apart from these two states, the devices may be unusable to the battery exhaustion. In this study Moore neighborhood is applied. As it is a decentralized network management, each node, even if it is in off state becomes active in each time unit and counts its active neighbors. The authors observes a life time increase at four times of the non-controlled topology management state while maintaining 80% coverage area all the time.

3.3 The Network Architecture

In this work, the considered topology for the network of things covers an area which contains many smart devices that observe certain events and communicate with each other or with a server about their observations. Such an area is presented in Figure 3.2. There exist a large variety of IoT devices; daily used consumer electronics (TV, coffee machine, air conditioner etc.) and application based used and always active sensor devices (motion sensors, smoke sensors etc.) [26]. Despite the large varieties, these devices can be investigated under two major device types, i.e. trigger based devices (TBD) and periodic signal devices (PSD). The accuracy of this aggregation

of device types can be investigated using the famous example of the IoT network of a businessman who has a meeting at 8 *am*. Previous night, he sets his phones alarm clock to 7 *am* and installs his coffee machine and toast machine. At 6 *am*, telephone gathers the traffic flow speed via Internet and based on this knowledge, it changes the alarm clock. For example it pulls the alarm clock to 6^{30} *am* due to the low traffic flow speed. At 6^{35} *am*, while the businessman is in shower, telephone transmits a wake signal to the coffee machine and toast machine. At 6^{45} *am* both toast machine and coffee machine transmits their ready signal to the phone and the businessman starts his breakfast. At 6^{55} *am* telephone connects to the car and opens its air conditioner. At 7^{10} *am* the businessman is on his car and traveling to his meeting. The reality of this scenario is doubtful, however, it helps to understand the difference between IoT devices. During the optimistic scenario of the businessman, the connection between coffee machine and telephone is a great example for a connection between a TBD device and a controller. This type of communication does not contain any specific data and more like a trigger signal that is used to wake TBD and wait it to observe the expected event. When it observes the event, which is the "hot coffee" for this specific case, it transmits another trigger back to the controller. The communication between the toast machine and the telephone is also a TBD communication example. However, the communication between the telephone and the car is the second type of communication, a PSD-to-Controller communication. The car contains many possible functions and the telephone has to define the specific attributes of the asked function like the name of the function and expected variables. For example for the considered scenario the telephone has to transmit that the air conditioner should be opened and it should be set to 22°C degree. So different than TBD communications PSD has to transmit complete data packets to controllers and receive specific data packets. Battery consumption is the most important parameter for TBDs and the goal is to increase the duration of these devices while maintaining the coverage area. The second type of users, PSDs, have to send a periodic life signal to the base station. If there exist any server request for these devices they transmit the necessary data. In other cases they only transmit this life message. The coverage area is not important for this devices. Durability is the main concern for these devices and of course the battery consumption is the main reason of the battery exhaustion of these devices. With these objectives we defined three states for devices, namely *sleep*, *active* and *passive*. In sleep mode

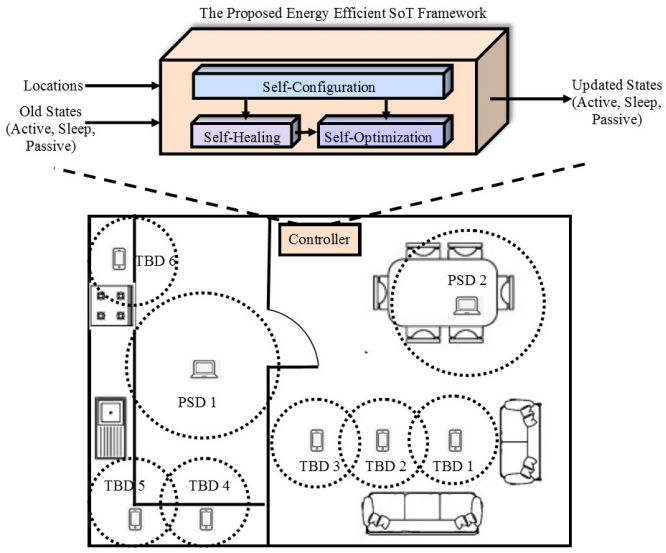


Figure 3.2: An Example IoT Network Topology with SoT Integration.

devices do not observe the area and all the unnecessary energy consumptions are turned off. In active mode, devices are working and observing the area. Finally in passive mode, the battery of devices are exhausted and devices are completely turned off. These three states are the only states that a device may exist.

Figure 3.2 is our example observation area. As seen in the figure, there exist 8 things, 6 TBDs and 2 PSDs in this network. In a real scenario case there exist more than 20 devices in IoT. Our the main objective is to keep the coverage area as high as possible for a long time. A practical idea to increase the coverage area can be increasing the number of devices. Even though this increases the coverage area, the lifetime of all these devices will be short due to the battery limitations. In this practical case by increasing the number of devices, coverage improvements are maintained by the sacrifice of energy. However, as can be seen in Figure 3.2, there could be cases in the network when putting a device in sleep mode does not create a high fall in the coverage area, however, decrease the energy consumption of the network. As an example, in Figure 3.2, 1st, 2nd and 3rd devices are mostly covering the same area. Instead of working all of them together, the 2nd device may be putted in sleep mode and 1st and 3rd devices may be kept in active mode. After batteries of 1st and 3rd devices are finished, the 2nd device may be activated and by this scheduling technique, the energy consumption can be decreased [38] and the durability of the network can be increased by a small loss of coverage area.

The objectives of the IoT devices should be taken into consideration to avoid a sacrifice

in network performance to gain the energy efficiency. PSD devices do not have to keep in active mode as they do not have to make an observation in their area. While there is not any service requests, these devices can be sent to sleep mode. As these devices do not consume much energy, during their sleep mode, the main energy killer process is the transmission. The main concern in this study for PSDs are their interference with TBDs. As they may both try to send information at the same time, interference could destroy both of messages. Transmission repetitions will consume power and cause decrease on the durability. Because of this reason, when a PSD gets active, other TBDs will have to get sleep mode to prevent interference. In this study interference between PSDs is not covered. For TBDs, as these devices are not communicating without a trigger, the energy optimization can only be achieved by putting these devices into sleep mode. However, as the main goal of these devices is to catch these specific triggers, as the number of active nodes decreases, the probability of observing a trigger decreases. This trade off between durability and the success of the observation is critical.

For most of the network topologies, the IoT network does not have to cover the whole network area to guarantee a certain amount of event observations. In these situations, to increase the durability a lower number of devices, N, can be enough to fulfill the expected event observations. If x binary random variable denotes the existence of an event in the observation area, A, and C denotes the observed area, the probability of an event existing in C if existence of the event is known, $P(C|x)$, can be calculated using (3.1)

$$P(C|x) = \frac{P(C) \times P(x|C)}{P(x)} \tag{3.1}$$

as x and C are discreate events $P(x|C)$ will be equal to $P(x)$ and Eq.3.1 will be equal to

$$P(C|x) = \frac{P(C) \times P(x|C)}{P(x)} = \frac{P(C) \times P(x)}{P(x)} = P(C) \tag{3.2}$$

As presented in (3.2), the probability of occuring an event in the observed area is equal to the observation rate of the area. From this point of view the probability of observing an event is presented in (3.3).

$$P(C|x) = \frac{N \times \pi \times R^2}{A} \tag{3.3}$$

where R is the radius of coverage area for a single TBD. In (3.3), "$N \times \pi \times R^2$" term denotes the total observed area by N devices. However, as can be seen in Figure 3.2, the actual total covered area does not always equal to the practical covered area as some of the devices covers the same region. The actual covered area is a multiplication of the practical covered area. So the probability of observing an event will be equal to (3.4).

$$P(C|x) = \frac{\psi \times N \times \pi \times R^2}{A} \tag{3.4}$$

where ψ is the rate of the actual covered area over the practical covered area and calculated as (3.5).

$$\psi = \frac{\sum_{n=1}^{N} \pi \times \ R_n^2}{N \times \pi \times R^2} \qquad \forall n \in N \tag{3.5}$$

Using (3.4), the number of TBDs needed to expect to observe P rate of all the events will be,

$$N = \frac{P \times A}{\psi \times \pi \times R^2} \tag{3.6}$$

where P is the probability of observing an event in observed region, more generally the rate of events that is expected to be observed, and ψ is the actual coverage area constant. As can be seen from the definition the expected number of observed events is equal to P, (3.7), and the standart deviation is equal to (3.8).

$$E(C|x) = P(C|x) \tag{3.7}$$

$$\sigma = \sqrt{P(C|x) - P(C|x)^2} \tag{3.8}$$

If we consider (3.6), (3.7) and (3.8) together, the number of active TBDs, to observe a constant rate of over all events, $E(C|x)$, is equal to N. However, the observation rate cannot be guaranteed due to the probabilistic distribution of event locations and a standard deviation, σ, may occur between the expected rate of observed events and the actual rate of observed events. The σ term also indicates the number of possible missed events by putting some of the devices in sleep mode.

As stated earlier we defined three states for the devices, sleep mode, passive mode and active mode. Sleep mode is the minimum energy consuming state for a device while passive mode indicates that the device can no longer function due to the battery exhaustion. The energy consumption for a device in passive mode is equal to 0. For a device in active state, three possible actions are defined, being idle, receiving and

transmitting [38]. The idle action is the case when a device observes its region. This is especially defined for TBSs and it indicates that the device is waiting for an event, a trigger. Two communication actions are defined, i.e. transmit and receive. The energy consumptions of all these two state and three action is presented in Table **??**. As can be seen, wireless transceiver power consumptions that are presented in 802.11*b* are used for TBDs and 802.11*a* for PSDs [38]. All the used parameters are presented in Table **??**.

Table 3.1: Power consumption model for different modes and devices.

Mode	TBDs	PSDs
Sleep	132 mW	132 mW
Idle	554 mW	990 mW
Receive	726 mW	1320 mW
Transmit	1089 mW	1815 mW

3.4 The Self-Organized Things Framework (SoT)

The proposed framework, SoT, has three different focuses;

- Decreasing the energy consumption,
- Increasing the durability of the network,
- Maintaining self-management and by this way decreasing the human interaction.

It is a known fact that the high energy consumption is decreasing the life time of the devices and also decreasing the durability. Due to this, the energy consumption is the main problem that needs to be taken care of to increase the durability of the network. To decrease the energy consumption, the number of active sensors can be decreased to a number, N, that is calculated for an expected rate of observed events. In literature there exist many algorithms that is working with a similar idea, however, the spatial distributions and the actually covered areas of these devices are not covered. For many cases a random selection mechanism is ended with low event observation rates. To increase the observation rate while increasing the durability, we are presenting a self-organized things (SoT) framework. As can be seen in Figure 3.2, the three main concepts of self-organized structure, self-configuration, self-healing and

Table 3.2: Symbols and their definitions.

Symbol	Definition
X	Binary random variable for the existance of a event
ψ	Actual coverage area constant
δ	Actual coverage area for the unit energy
ξ	Conflict parameter
ϕ	State of a device
A	Observed Area
R	Coverage radius
R_{ij}	Euclidian distance between two devices
N	Number of devices
$N(t)$	Number of active devicesat time t
$E_T(t)$	Total energy consumption at time t
C	The observed area
P	Rate of observed events
(x,y)	Location coordinates of a device

self-optimization, is presented in this work. The inputs of SoT is the locations and the statuses of each devices. The objectives of our work can be modeled as an optimization process. The actual coverage area for the unit energy, δ, is presented in (3.9).

$$\delta = \frac{\psi \times N(t) \times \pi \times R^2}{E_T(t)} \tag{3.9}$$

where $E_T(t)$ denotes the total energy consumption in the network at time t. Due to the traffic changes, triggers and service request, the total energy consumption of the network is a dynamically changing parameter. The number of active devices, N, changes with time as the conflict parameter, ψ, changes according to the active nodes. The objective of SoT framework can be presented as an optimization process as presented in (3.10).

$$\begin{aligned} &Maximize \quad \int \frac{\psi \times N(t) \times \pi \times R^2}{E_T(t)} \times dt \\ &Subject\,to \qquad N(t) \geq N \end{aligned} \tag{3.10}$$

The optimization objective shows that the δ term keeps increasing while the number of active nodes increases. However, if the number of active nodes passes a critical value,

N_{cr}, conflicts begin and the ψ term decreases. As the energy consumption of an active node does not change with the active covered area, the total energy consumption of the network keeps increasing. After this critical N value the δ terms keeps decreasing. The maximum δ value can be reached for this N_{cr} parameter. However, there could be such a case when N_{cr} is lower than the necessary number of active devices, N. At this time, to fulfill the observation rate the number of active devices increases inspite of the energy efficiency loss. The proposed SoT framework is maintaining this optimization problem according to a basic sleep and wake up methodology. To put a device to sleep state, SoT framework uses two decision parameters namely, the local indicator of spatial autocorrelation coefficient and the conflict parameter. As it is explained in the further section the conflict parameter is different from the conflict constant, ψ. After self-management process, SoT framework outputs the states of all devices.

3.4.1 Self-configuration

The SoT framework starts with the self-configuration structure. As previously stated the inputs are the states and the locations of the devices. The self-configuration structure is a pre-data-processing structure that prepares the input data for the optimization. The self-configuration algorithm is presented in Algorithm 1. As can be seen from Algorithm 1, two decision parameters are calculated in this structure. These are the conflict parameter, ξ, and the spatial correlation parameter, I_K. The

Algorithm 1 Self-configuration algorithm.

Require: (x, y)
Ensure: ξ_i, I_k

```
for n ← 1 to N do
    if TBD then
        φ ← 1
    else
        Send Life Signal
        φ ← 0
    end if
end for
Calculate ξ
Calculate I_K
```

self-configuration is putting all workable, not dead, TBDs to active state while it is putting all PSDs to sleep state. As stated earlier the coverage area is the main concern for TBDs. So in topology design, for the most optimal solution self-configuration

is activating all the devices. Then the conflict calculation and spatial correlation calculation is calculated only for TBDs.

3.4.1.1 Conflict calculation

The main challenge in IoT network configuration is preventing the selection of devices that is covering the same area. For example in Figure 3.2, if TBDs 1 and 3 is in active state than putting TBD 2 into active state is not necessary as the most of its observation region is covered by TBD 1 and TBD 3. However, there could be also cases like TBD 4 and TBD 5 in Figure 3.2, where the conflict between nodes are not very high and in case of necessity they can be both in active state. So there exist a decision problem in the conflicts. To overcome this decision problem, we define a conflict parameter that is calculated for each TBDs in the network.

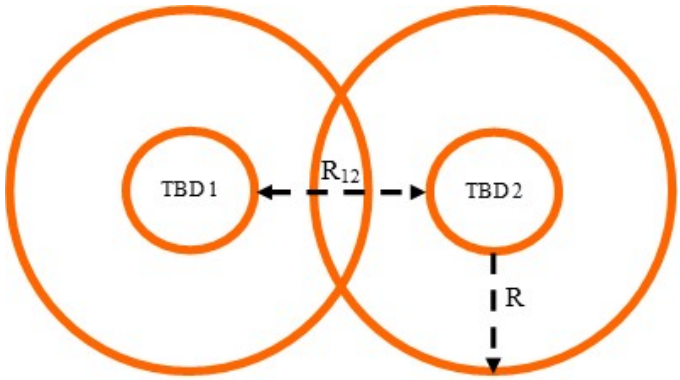


Figure 3.3: Conflict parameter calculation.

The conflict parameter, ξ, is kept in the network controller and is calculated based on the locations of each device. In Figure 3.3, there exist two TBDs. The distance between these TBDs are R_{12} where the coverage area radius is R. There could be two possible cases, R_{12} is smaller than $2R$ or R_{12} is greater or equal to $2R$. The first case, $R_{12} \leq 2R$, indicates that there exist a conflict and this two device is covering the same area. Then the conflict parameter is calculated. Conflict parameter changes between 0 and 1. Value of 1 indicates that there is no conflict and the value of 0 indicates that this two devices are covering the same area. the total conflict parameter for i^{th} device is the sum of all the conflict parameters between i^{th} device and the jth device, as presented in (3.11).

$$\xi_i = \sum_j \frac{R_{ij} \times 1(R_{ij} < 2R) + 2R \times 1(R_{ij} \geq 2R))}{2R} \forall i, j \in N \tag{3.11}$$

As can be understood from (3.11), conflict parameter indicates how much unique area the device is covering and higher parameter values are better in decision process.

3.4.1.2 Spatial correlation calculation

Even though the conflict parameter presents a great knowledge to make a decision many cases it is not sufficient. For example in Figure 3.2, for TBD 4 and TBD 5, the conflict parameters are equal. So the decision process that based on only conflict rate of the device will randomly activate one of these devices. However, for many cases this random decision is not efficient. For example, if TBDs are trying to observe the motion in the region being far from the rest of the TBDs improves the change of observing the movement. For most of cases, giving the activation priority to the farther TBD is the most optimal decision. To measure the spatial distribution of devices in 2D space, we use spatial distribution parameter [39], I_k, for each device. In Figure 3.4, an example distribution of devices in the $2D$ space is presented.

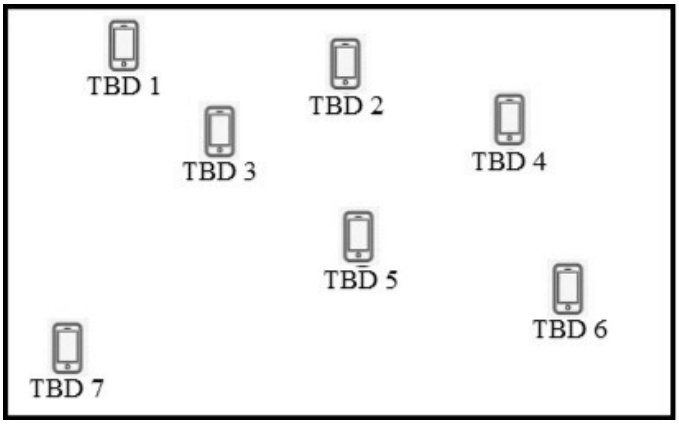


Figure 3.4: Example case for spatial distribution of TBD devices.

As definition, spatial distribution parameter, I_k, shows how a special attribute changes with location. In this study, we are trying to observe how the active state devices distributed in $2D$ space does. More specifically, the I_k parameter, which is defined for each device separately, gives an idea of device′s position in the $2D$ space of active devices. I_k formula is presented in (3.12).

$$I_k = \frac{\phi_k \times \sum \phi_i \times R_{ki}}{\sum \phi^2} \quad \forall k, i \in N \tag{3.12}$$

where ϕ denotes the state of the device and R_{ki} denotes the Euclidian distance between element i and k. We defined two values, 0 and 1, for the ϕ attribute. As stated earlier three state defined for a device namely, active, sleep and dead. The ϕ parameter gets

value of 0 for both of sleep state and dead state and gets value of 1 for active state. w_{ij} parameter represents the distance between device i and device j. As can be easily understood the spatial correlation parameter, I_k, in Figure 3.4 is now presenting the correlation of active nodes in $2D$ space and for each device, I_k presents the correlation of other active devices around it. It can also be seen that if device is in sleep mode or passive mode, device′s spatial correlation parameter will be equal to 0.

It can be understood from (3.12) that the optimal decision is activating a device with higher spatial correlation coefficient as it indicates that device is covering a more different part of the region than the rest of the devices. For the example, spatial distribution presented in Figure 3.4 , functioning TBDs $1-6$ is not efficient as they are covering close areas. For many cases, to increase the change of event catching, functioning TBDs that is far from each other is more optimal. For example if TBDs are smoke sensors, if an event occur in the coverage area of TBD 3, it can also be observed by TBD 1 and TBD 2. So functioning these three devices together is inefficient as there exist no increase in change of event catching but there exist an increase in energy consumption. The most optimal configuration is activating TBD 7 and TBD 3 simultaneously as it increases the change of event catching.

3.4.2 Self-optimization

Self-optimization is the part where the most optimal configuration of the active devices is founded. Self-optimization receives the I_i parameters and ξ_i parameters of the devices in the network from the self-configuration. Specifications of these parameters can be presented as,

- ξ_i, conflict parameter, gives the knowledge of how much unique area the device is covering.
- Higher ξ_i parameters are better as they show that device is covering an uncovered area.
- I_i, spatial correlation parameter, gives the knowledge of how the active state devices change within $2D$ space.
- Higher I_i parameters are better as they present that device i is covering a less covered fraction of the region.

- I_i does not give a complete knowledge about the conflicts between devices. If two device are far from the rest of the devices, even they are covering completely the same area, their I_i parameters are going to be large.

As stated earlier one of the most important objective of this work is an energy efficient and high coverage rate topology configuration and we are measuring the optimality with this objective. To fulfill this objective, we are using both I_i and ξ_i parameters. The self-optimization algorithm is presented in Algorithm 2. The first step of the self-optimization algorithm is listing all the devices in the network. There exist two lists, one is based on I_i parameters and the other one is based on ξ_i parameters. Both lists are created in the decreasing order so the first terms are presenting the highest valued devices. Another important parameter in self-optimization is the number of minimum active devices, N, to observe certain rate of events in the network. The N value is presented in (3.6). However, the ψ term changes with the locations of the active parameters. The problem in this definition is the dynamic nature of $N(t)$. So during the run time, ψ calculation is problematic. Instead, we are using the ψ values that is calculated after the optimization process in the previous topology change. More specifically, in time t, to calculate the $N(t)$ parameter, we are using the $\psi(t-1)$ term. ψ parameter is a normalization parameter to calculate the actual covered area from the practical covered area. Using the ψ term from the previous state will cause a decrease in the precision of the calculated device number as the previously observed network topology at time $t-1$ has changed and many of the active devices in the previous topology are in passive in the network topology at time t. For a far spread IoT network topology, usage of $\psi(t-1)$ is insufficient. As the calculated covered area at time t will be smaller than the real covered area, the calculated number of devices will be inefficient and will cause a sharp decrease in the observed event rate. In this study, we are observing a dense IoT network topology, which contains many IoT devices covering the same area. Due to this, the usage of ψ parameter from a previous state will not decrease the precision of the management.

After listing all the devices, the selective activation process is started. The activation process primarily uses the ψ list. As can be seen in Algorithm 2, if the conflict parameter value of the device is equal to the number of devices, as this indicates that the ith device does not conflict with any other devices, the device is activated and the

Algorithm 2 Self-optimization algorithm.

Require: ξ_i, I_k
Ensure: ϕ

```
List devices
Calculate N(t)
while N_actv < N(t) or not All Devices do
    if ξ_i = N_actv then
        φ ← 1
        N_actv + 1 ← N_actv
    else
        if ξ_i = ξ_j then
            if I_i > I_j then
                φ_i ← 1, φ_j ← 0
            else
                φ_j ← 1, φ_i ← 0
            end if
        else
            if ξ_i > xi_j then
                φ_i ← 1, φ_j ← 0
            else
                φ_j ← 1, φ_i ← 0
            end if
        end if
        N_actv + 1 ← N_actv
    end if
end while
if N_actv < N(t) then
    for N(t) − N_actv>0 do
        if φ_i = 0 then
            φ_i ← 1
            N_actv + 1 ← N_actv
        end if
    end for
end if
Update ψ(t)
```

number of active devices is incremented by 1. If the conflict parameter is smaller than the number of devices in the network, then there exist at least one other device that this device have conflicted. In this case two possible situations are possible, equal conflict parameters between conflicted devices or different conflict parameters. If the conflict parameters are different the higher conflict device is activated while the lover one is sent to sleep state. In case of equal conflict parameters, I_i list is checked. The I_i parameters of conflicted devices are compared and the higher one is activated. The rests are sent to sleep mode. For example, network topology that is presented in Figure 3.2, the decision process for TBDs are critical for two group of TBDs, $1-2-3$ and $4-5$. The TBD 6 as it does not have a conflict with others, it is directly activated. TBD 1, TBD 2 and TBD 3, they have conflict with each other. However, comparing the conflict parameters of TBD 1 and TBD 2, it is obvious that $\xi_1 > \xi_2$. So in decision process, TBD 1 is going to be activated while TBD 2 will be kept in sleep mode. As the TBD 2 is sent to sleep mode, TBD 3 will be activated, too. For the second group, TBD 4 and TBD 5, it is obvious that their conflict parameters are equal to each other. So their I_i parameters are going to be compared. It is obvious that $I_5 > I_4$ so the TBD 5 is going to be activated while the TBD 4 is sent to sleep mode.

The comparison of the I_i parameters could be seem a little confusing for the second group of TBDs, 4th and 5th. However, two pre-processes, continuing the activation process according to the queue in conflict list and the activation of all TBDs in the self-configuration, guarantee the optimality of the comparison. As the I_i comparison is only done for the conflicted ones, the devices that is going to be sent to sleep state does not create a comparison failure because the effects of this device can be ignored. Following the Algorithm 1 or Algorithm 3, the Algorithm 2 is executed at the network topology changes, i.e. device's active/passive state changes and initialization case. As the complexity of the proposed framework is another challenge, the main optimization framework needed to be investigated in terms of complexity. As can be seen in Algorithm 2, the complexity of the algorithm except for the ψ calculation is equal to $O(N)$. However, as the calculation of ψ parameter is performed for each device couples, this part's complexity will be $O(N^2)$. From this point of view, the complexity of the overall Algorithm 2 is $O(N^2)$. However, as stated earlier this is

because of the applied calculation method of ψ parameter, using a simpler calculation technique, the complexity of the algorithm will decrease.

3.4.3 Self-healing

After the self-optimization process, the network reaches its most optimal state. However, as stated earlier the battery lifetime is a big problem in IoT. After some time from the activation of a device, its battery power is exhausted and due to this exhaustion, device sends out a passive signal and sends itself to the passive state. At this case, SoT framework re-optimizes the network. The network durability is increased by the self-healing mechanism. By durability, we indicate the total time that the area is observed. By the self-managing process, the network always exist in the most optimal topology in terms of total covered area and energy efficiency.

When a device sends out a passive signal, the network has to be optimized from the beginning as the conflict parameters and the spatial correlation parameters are going to change. Self-Healing mechanism received the passive message and updates the device list by deleting the passive device from its list. After that the self-healing process passes the updated I_i parameters and the ξ_i paraeters to the self-optimization process and based on these values the new network topology is decided. The algorithm of self-healing is presented in Algorithm 3.

Algorithm 3 Self-healing algorithm.

Require: $Passive\,signal\,from\,i^{th}\,device$
Ensure: ξ_i, I_k

```
Remove i from list
N − 1 ← N
for n ← 1 to N do
    if TBD then
        φ ← 1
    else
        Send Life Signal
        φ ← 0
    end if
end for
Calculate ξ
Calculate I_K
```

As stated earlier, if there is no server request, PSDs only send a life message and then put itself into sleep state. A possible problem here is the case when both a PSD

and a TBD tries to communicate at the same time. Due to interferance, they have to retransmit and as stated previously, transmission is the most energy consuming process for both PSDs and TBDs. To prevent this inefficient case, we give priority to PSD communications. If the PSD needs to communicate, it sends a call to each TBD that has conflict with PSD. And then it communicates. If it sends a life signal, TBD sets a counter and until this counter reaches 0, it stays in sleep mode. After counter reaches 0, it passes to active mode again. If PSD is responding a server request then TBD waits for another call from PSD and until this call it passes to active mode. Note that PSDs check their remaining battery power before they send a signal to TBDs. If their power is not sufficient then they sent a message to the controller and inform it that they are passive.

3.5 Performance Evaluations

The success of the proposed SoT framework is investigated in terms of total actual coverage area and the total coverage area per energy unit, δ. In (3.6), the minimum number of active devices to guarantee the observation of a constant event rate is presented. During the calculation of this N parameter, we accepted a uniform probability distribution of the events in the observed area. The main concern of this study is to optimize the lifetimes of devices while maintaining a high coverage area. We accepted that the devices are battery powered and they cannot increase their power during the simulations. They consume static energy amounts for each of their states. Even for the most optimal network topology in terms of energy consumption, the total energy consumption function ($E(t)$) of the network contains a static part and a fluctuating part. The static energy consumption is due to the topology of the network, and proportional to the number of active devices. However, the fluctuating part of the energy consumption is because of the communication of the devices. The static energy consumption of the network is unavoidable due to the necessary number of active devices. However, the communication part varies and changes the performance of the network. In the most optimal network topology ($\psi = 1\ \forall N_i$), the traffic rate causes no changes as devices are covering completely distinct locations. However, for the worst network topology ($\psi = 0.5\ \forall N_i$), traffic load can measure huge differences in the lifetime of devices, as the number of unnecessary communications triggered by

the same event will increase enormously. By this way, the communication rate, more generally the traffic rate is highly important to determine the performed optimization process. Due to this importance, in simulations, addition to the performance evaluation of SoT framework, we also present the effects of different traffic rates of PSDs and TBDs on network performance and energy efficiency. By traffic rate we are implying the server requests and triggers that TBDs and PSDs receives and their responds. In the simulations, the effects of traffic rate are observed by changing the received traffic requests using a probabilistic approach. We defined two different probability variable, p_1 and p_2 where p_1 is used to create PSD traffic and p_2 is used to create TBD traffic. TBDs and PSDs are randomly located in the region. As the coverage area of a single

Table 3.3: Network parameters

Parameter	Value
A	$200m^2$
R	$2m$
N_{TBD}	60
N_{PSD}	10
E	$50W$

device is equal to $12.57m^2$, the total observation area of the TBDs is $754.2m^2$ which is larger than the observation area so there will be 3.77 TBD in each TBD location. This high density of TBDs over the observation region guarantees conflicts over coverage areas of distinct TBDs and makes this network topology sufficient to determine the performance of the proposed SoT framework. The interference coefficient is dynamically calculated through the simulations and a dynamic ψ parameter is reached. As previously stated, all devices are covering an area of $\pi \times R^2$ in the space. However, the devices can cover the same area so the actual covered area equals to $\psi \times \pi \times R^2$. ψ parameter is theoretically the actual covered area divided by $\pi \times R^2$. For simplicity in simulations instead of the formula presented in (3.5), we used an estimated equation that is presented in (3.13).

$$\psi_i = \frac{\Sigma_j(0.5 \times log_{2R}(R_{ij}) \times 1(x < 2R) + 0.5 \times 1(x > 2R) + 0.5}{N_{active})} \quad \forall i, j \in N \tag{3.13}$$

$$\psi = \frac{\Sigma_i \psi_i}{N_{active}} \qquad \forall i \in N_{active} \qquad \textbf{(3.14)}$$

where x is the distance between devices. (3.13) is reached from the idea that if the distance between two nodes is greater than $2 \times R$ than the interference coefficient will be equal to 1 and if the distance between this two nodes is equal to 0 then the interference coefficient will be equal to 0.5. As can be seen from this definition, interference coefficient is calculated for two devices case. The interference coefficient is calculated distinctly for each user couple and the mean value of their summation is used as the interference coefficient. More specifically, for the network in Figure 3.2, while calculating ψ_2, we first checked the conflicts between TBDs $1-2$ and then TBDs $2-3$ and other active TBDs in the network. Then we take the mean value of this ψ_{2j} parameters. Finally, all the ψ_i parameters are added and the mean value of this parameters is calculated by using (3.14).

3.5.1 Performance verification

The success of the framework is measured in terms of total actually covered area in the region and actual covered area per energy. In the simulation, as stated earlier we used 60 TBDs and 10 PSDs with battery power of 50 *Watt* each. The change of total actual covered area is presented in Figure 3.5. As stated earlier, the minimum energy consumption, sleep mode energy consumption, is equal to 0.992 *Watt*. With a simple calculation, it can be seen that the maximum lifetime without an energy efficient scheduling, which can only be achieved by always staying in sleep state, is equal to 50.4 hour. The region is 200 m^2 and it is the maximum coverable area. The expected

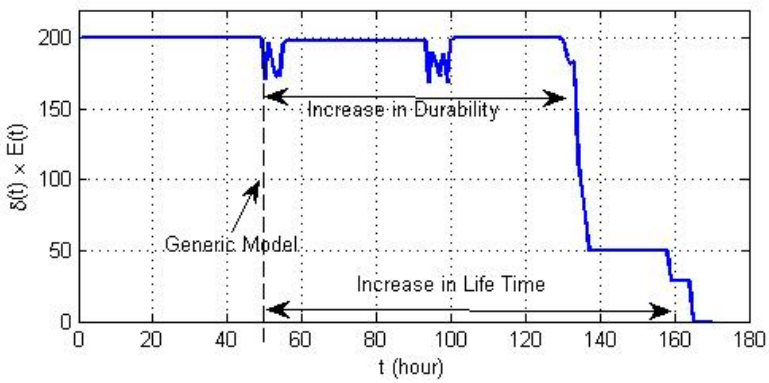


Figure 3.5: Increase in durability.

probability of event observation is static and equal to 95%, indicating that we expect to

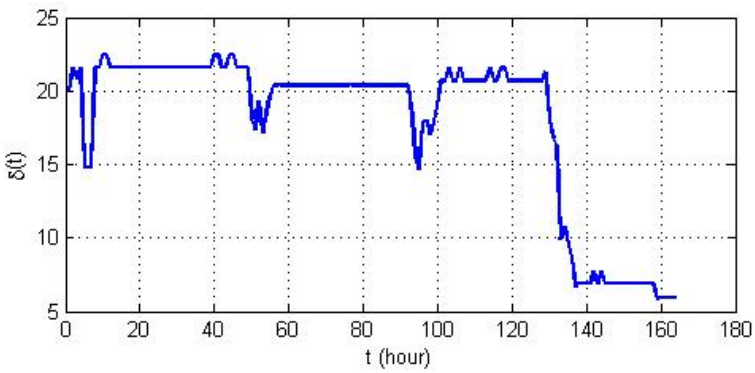


Figure 3.6: Total covered area per energy.

observe the 95% of overall events that happened in the region. The event distribution through the region is accepted as a uniform distribution. More specifically, probability of observing an event in each location ($p_{eventoccurance}$) is equal and $p_{eventoccurance} = 1/A$. As it is presented in Figure 3.5, with our proposed framework, for the first 125 hour, the covered area is equal to 200 m^2 which covers 100% of the region. As our objective is the coverage of 95% of the overall network, which is equal to 190 m^2, we accepted this as a border for our durability calculations which happened in 133 hour. After 160 hour the covered area falls to 20 m^2 which is the 10% of the coverable region. We accepted this 10% coverage line as the borderline of the lifetime. The limited battery sources of TBDs and the end of their lifetime cause these fall. As told earlier, we used 60 TBD device. According to the Figure 3.5, the durability is increased 150% and also the lifetime is increased 220%.

In Figure 3.6, the actual covered area per energy is presented. Our objection is to keep this value as high as possible as it show how energy efficient our system is. If this term is low that indicates that we are keeping some unnecessary devices in active state. It is obvious in Figure 3.6 that, during the simulation, the optimal network configuration is renewed for four times. Even though first three configurations presents the same coverage area, the energy efficiency decreases smoothly. At the first configuration the network based energy efficiency is around 23 m^2/W while after the third optimization it is around 20 m^2/W. This small decrease is because of the high device opportunity at the first optimization. The network controller can choose the most optimal network configuration easily. In the following optimization cycles, the number of live devices decreases and causes the selection of sub-optimal network topologies. Figure 3.6 shows that the proposed system is working in a stable state around 21 m^2/W. When

Figure 3.5 and Figure 3.6 is investigated together it also proves our previous statement about the decreasing coverage rate. As the coverage rate per *Watt* does not change the only reason of this coverage fall in Figure 3.5 can only be caused by the lack of devices. This results prove that our proposed framework fulfills the expectations and increases the both coverage area and durability of the network.

3.5.2 Effects of connection requests

In the proposed model, devices are consuming a very limited power accept for their communication intervals. This power consumption causes a constant life time duration. The fluctuations in their lifetime are mainly caused by the unnecessary communications of devices. In this study we proposed a novel scheduling framework that controls the states of devices according to their distribution. The proposed framework presents some privileges to PSDs over TBDs. Due to this privileges, PSDs and TBDs communication rates changes the energy consumption and eventually changes the lifetime of devices. As the fluctuations in the energy is a result of communication rate the energy consumption of the network under different communication rates has to be observed. In order to evaluate the success of the proposed framework, the effects of the traffic load are investigated. By traffic load we mean the integration of three concepts, the number of triggers for TBDs, the number of server requests for PSDs and the life signals of PSDs. So far we created these requests using a probabilistic approach. With probability p_1, we created the server request and with probability p_2, we created a trigger. So far these traffic was created statically with p_1=0.5 and p_2=0.2. However, in order to come up a complete conclusion, we have to observe the effect of changes on the traffic load on the framework. For this reason, we

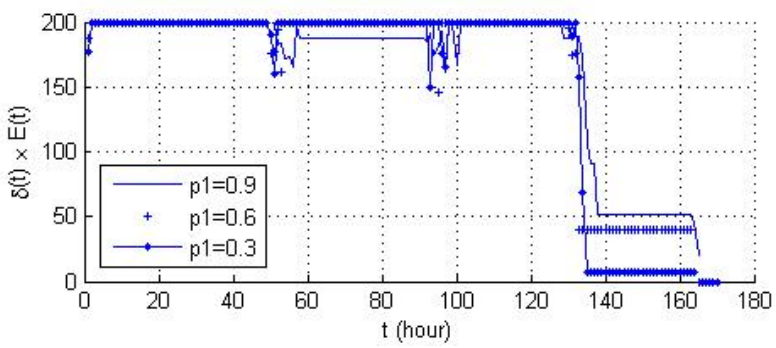


Figure 3.7: Total Coverage Area Change with PSD Traffic.

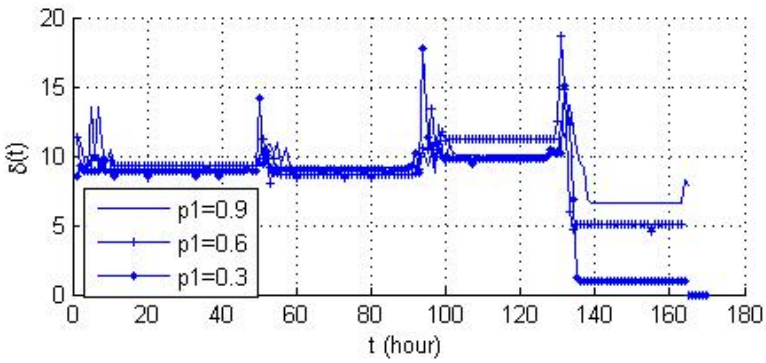


Figure 3.8: Total Covered Area per Energy change with PSD Traffic.

observed the total coverage area and the coverage area per energy for different traffic loads. To change the traffic, we changed the probabilities of requests and triggers, p_1 and p_2. The results for different p_1 values are presented in Figure 3.7 and Figure 3.8. In Figure 3.7, the total coverage area change according to the PSD traffic is presented. The changes in the PSD traffic do not cause any big change in terms of total coverage area. However, between 130th and 160th hours, the higher PSD traffic results in a higher coverage area. This is mostly because of the privileges of the PSD devices. The PSD devices put the TBD devices into stand by position as they are communicating. The TBDs are consuming a very little power during this time interval. In Figure 3.8, the energy efficiency of the network is presented. The energy efficiency is defined as the energy consumption to cover the unit area. This result also proves that high communication rates of PSDs do not actually decrease the energy efficiency during their lifetime. However, it is also visible that the energy efficiency at the end of their lifetime (between 130th and 160th hours) changes according to the traffic rate and higher traffic rates causes better energy efficiency. This is mostly because the privileges of PSDs over TBDs. As traffic rate of PSDs increases more TBDs are staying active state in this time interval. From these two result it is possible to say to increase the efficiency during the lifetime, higher PSD traffics are better. However, as PSD traffic causes an increase in the event miss to observe more event traffic must be low.

During this study, the performance is measured by the actually covered area, which can directly change with the number of active TBDs. The effect of TBD traffic on total coverage area and energy efficiency is a main concern, as the network topology should not lose its optimality or efficiency by the changing traffic. During the simulation, the traffic rate of the TBDs are changed by changing the p_2 parameter. In Figure 3.9

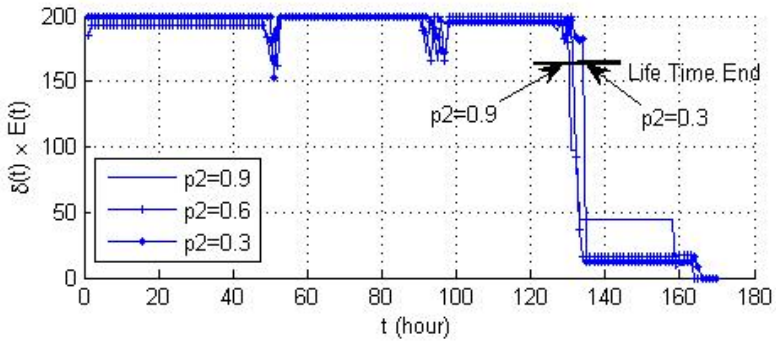


Figure 3.9: Total Coverage Area Change with TBD Traffic.

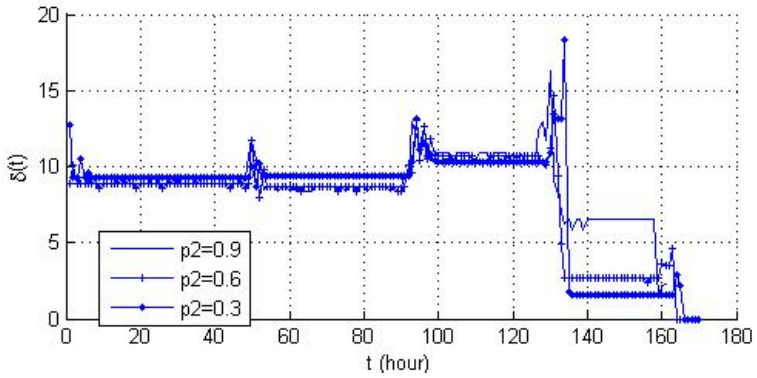


Figure 3.10: Total Covered Area per Energy change with TBD Traffic.

and Figure 4.5, the effect of traffic rate on total coverage area and energy efficiency is presented. As expected, increase in network traffic decreased the lifetime of devices. However, it is also observed that the higher traffic rate increases the energy efficiency and the total coverage area.

3.5.3 Effects of node density

In the previous sections, it was stated that the TBD count is a strict border in the lifetime of the network. The proposed network schedules the TBD states to achieve the maximum network durability with the highest event observation rate. Based on this definition the effect of node density on the network durability is also important. In the previous simulations, the number of TBDs (nodes) is assumed to be static and equal to 60. In Figure 3.11, the effect of node density on overall network durability is investigated. The number of nodes is changed from 60 to 160, which is a 167% increase in the number of nodes. However, this huge increase in the number of nodes resulted in 62.5% increase in durability of the network. Additionally, the increment trend of the durability with the number of nodes is more likely a logarithmic increment

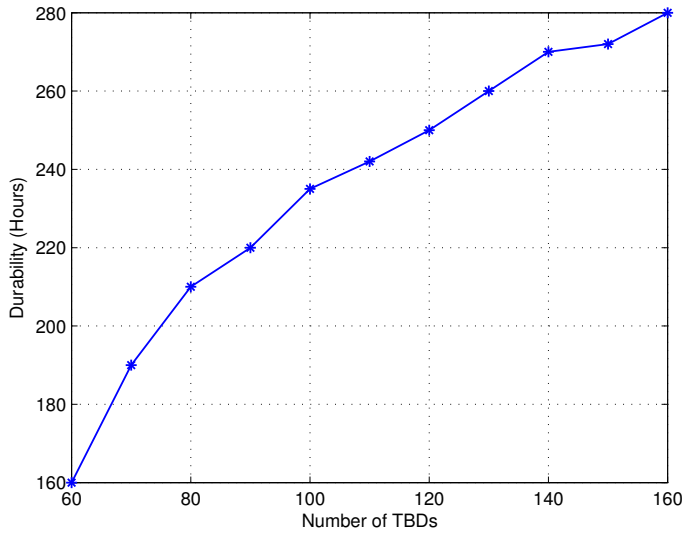


Figure 3.11: Durability change with the number of nodes

than a linear increment. It can be modeled as a logarithmic function with an upper bound at the infinity.

Theoretically, as each device covers an area of 12 m^2, 18 TBDs would be enough to cover the whole area and by this way the expected durability for a network containing 160 TBDs will be around 440 hour. However, the simulations shows that the measured durability will be 280 hour, which is smaller than the expected value. This is because of the two special attributes of the proposed framework. First one is the proposed framework's effort to cover the whole area. To cover the whole area the number of activated devices is higher than the theoretically calculated number, which decreases the expected durability of the network. The second reason is the density of the nodes. As the number of nodes increases, their unique coverage area decreases. As the unique coverage area decreases, the ψ parameter decreases which leads to an increase in the number of active devices. Due to this reason, the active nodes per time increases massively and this decreases the durability of the IoT network.

3.5.4 Discussion

During the performance evaluation part, the proposed framework is investigated in terms of energy efficiency, coverage area, traffic rate and node density. Based on these evaluations and the algorithmic complexity of the proposed framework the following results can be reached.

- The proposed framework can perform 150% increase in durability and 220% increase in the overall lifetime of the network. This shows that this framework can maintain the energy efficiency demand of IoT devices.
- The proposed framework can perform the selection of remote TBDs, which increases the detection of distinct events. This algorithm depends on the idea of continuous and discrete events. As continuous events, e.g. motion, follows a sequence, the algorithm tries to increase the detection of discrete events.
- Unlike the existing frameworks, the proposed model considers the three design parameters, i.e. total coverage area, distribution of devices in 2D space and distribution of events in 2D space, to create the optimial schedule.
- The proposed framework is effective for dense IoT networks with low traffic rate.
- Increase in node density has a negative impact on the durability trend. Even though, dense network topology (5 device per m^2) is necessary for network efficiency, a huge increase in density (10 device per m^2), causes a decrease in energy efficiency due to ψ parameter.

4. NEXT GENERATION BIO-INSPIRED SON DEPLOYMENT

In the previous two chapters, we proposed two different topology management frameworks that each one of them handles a different user type. However, as previously explained, both $I^2 - gSON$ and SOT has their own weaknesses and strongholds. These weaknesses can be summarized as;

- The need of global information in the beginning of the network determination and the missing controller concept in SOT that controls this inter-device communications.
- The possible worst case solution oscillations before the determination of the optimal solution which leads massive decrease in the QoS.
- The selection of complete sleep mode as an optimal solution which is a natural solution of the energy based optimization technique.

However, apart from these structural problems, the applicability of this network is doubtful. These two user types do not exist in separated wireless networks, instead, they exist in the same network and sharing the same resources. They are using different performance metrics, which states that single objectives are not acceptable in terms of performance optimization. Moreover, the usage of both of these algorithms in the same controller for different user types will increase the complexity which will eventually lead to low energy efficiency and low performance. Due to this reason the coexistence of these devices in the same wireless network is the main problem.

4.1 Purpose

Both the mobile devices and the other RF module equipped electronic devices have to coexist in the same wireless network and share the same physically constraint frequency range. Discrete central or external controllers for these structures increase the control signals and energy consumption even though they cannot actually propose a complete solution to the network topology problem [40]. From the existing topology

management point of view, the wireless network topology management is destined to a complete chaos as the speedily increasing data traffic generated by every kind of consumer electronics and the "tsunami of smart phones" is competing for the limited frequency resources [41]. However, it can also be possible to see this chaos as an opportunity, which can increase both the energy efficiency and consumer satisfaction. In the network topology management frameworks presented in chapter 2 and chapter 3, the networks have to fulfill the users (mobile devices or RF module carrying electronics) performance metrics with a limited data gathered from the same users. As the considered network topologies so far are accepted to be homogeneous in terms of user types, the gathered knowledge is usually insufficient. Combining this data insufficiency with the structural inadequacies, the network topologies are actually far from the optimal state of themselves.

The heterogeneous network topology in terms of user type presents a great change to deploy a network controller that can not only maximize the energy efficiency but also increase the consumer satisfactory. In this chapter, we are proposing a premise network topology manager that can cope with heterogeneous performance metrics while maintaining the energy efficiency. The main contributions in this chapter can be itemized as;

- A hybrid self-organizing network management framework is proposed that can cope with not only the heterogeneous demands of users but also compensate the performance-energy tradeoff with high user satisfaction and higher energy efficiency,
- The previously proposed self-configuration structure is developed with a dynamic antigen concept which helps the proposed framework to deal with the dynamic performance metrics and highly dynamic nature of the environment,
- A novel self-optimization framework is proposed that can shift its optimization objectives based on the dynamic nature of the user expectations and the environment,
- A novel self-healing framework that designs the network management policy of the SON deployment and adapting an optimal policy according to the time of the day

and the very rapidly changing spatial distribution of the users and their performance expectations,

4.2 Generic Assumptions

The proposed framework is a combination of different subjects and works from different disciplines. Due to this, we presented some assumptions that are useful for the design of the proposed model. Even though the outlier situations are not covered in this work, the expected effects of them can be founded in section **??**. The generic assumptions are as follows;

- There exist two kinds of user performance metrics in the considered network deployment, throughput and the number of observed event. For simplicity we accept that all the devices are observing the same event. The validity of this assumption is presented in Chapter 3.
- The throughput can be raised by increasing the number of accepted users while the number of observed events can be raised by increasing the total covered area.
- The user expectations varies through the day. Between 8 am and 5 pm the QoS demand in terms of throughput reaches a maximum and through this period the most important concern of the management is to maintain the highest throughput ratio.
- Events are distributed in the 2D space according to the Gaussian distribution. In previous studies for simplicity uniform distribution was accepted for event distribution in the environment. However, it is obvious that at some locations the probability of event occurrence is higher than other locations.

4.3 The Network Architecture

In this study the considered network topology should be investigated under two different network architecture. The investigated network architecture that contains a main base station and an unspecific number of small cells is presented in Figure 4.1. Both mobile devices and IoT devices coexist in the same wireless network. However, this coexistence is more complex than the one presented in Figure 4.1. The distribution of devices in a home area wireless network is presented in Figure 4.2. The

distribution of devices and their performance metrics are important to overcome the performance-energy efficiency tradeoff in the wireless network.

In Figure 4.2 and Figure 4.1, two types of users are presented, mobile users and IoT devices. The mobile users are throughput-concerned devices. They are requesting some bandwidths to transfer their packets to their connected base stations. In this study the other QoS metrics like latency or jitter are not covered. There exist a large variety of IoT devices; daily used consumer electronics (TV, coffee machine, air conditioner etc.) and application based used and always active sensor devices (motion sensors, smoke sensors etc.). Despite the large varieties, these devices are investigated under two major device type as presented in Chapter 3. The accuracy of this aggregation of device types is investigated in Chapter 3. In a realistic hybrid wireless network topology as presented in Figure 4.1, there exist vast number of IoT devices types. However, it is accurate to divide their connection types into two main kinds by masking the devices as TBDs and PSDs. This is mostly accurate as they can produce two main sorts of packets during their transmissions. Their unique identities and objectives related to these identities can be resolved in the application layer. Another important outcome of the presented scenario is the usage of businessman's telephone as a controller that somehow schedules all other devices. The telephone is another IoT device that can be controlled by other IoT controllers. The important part of this situation is that central controller concept in IoT is application based and can change according to the flow of events. However, in our designed framework we only considered a centralized main controller case in which the main base station is used as the main controller. It is responsible to increase the performance metrics of both of the IoT user kinds. TBD devices communicate through triggers and the only expectation from them is

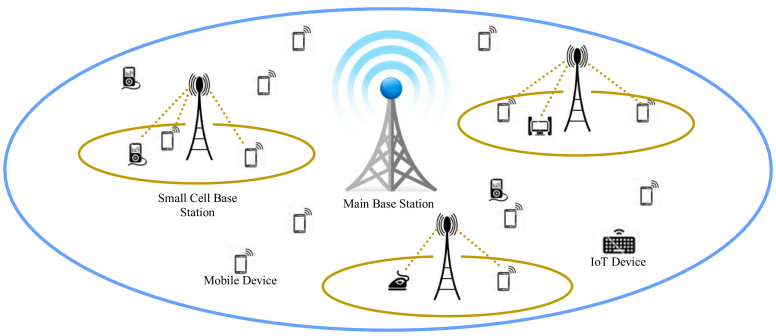


Figure 4.1: Considered hybrid network topology

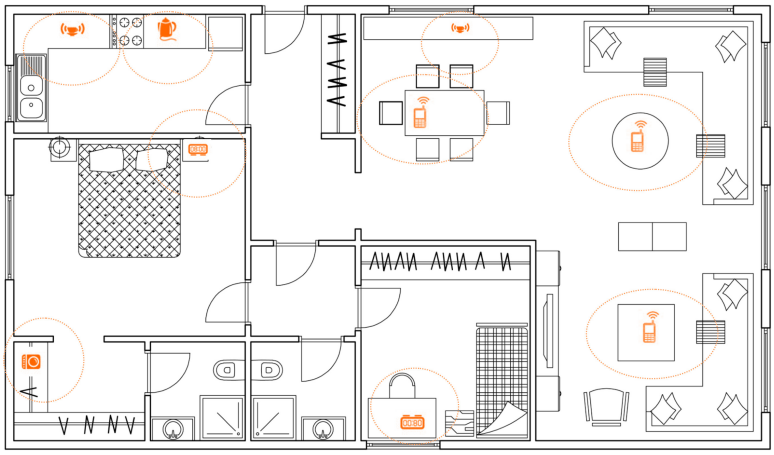


Figure 4.2: An example home network that contains both IoT devices and mobile users.

to observe as many events as possible. Due to this reason their throughput is not critical. What is more important for them is their durability. In this study we accepted that all devices are using batteries to create a sharp constriction on the performance metrics. If powered TBD devices were considered, then the optimal solution would be to activate all the TBDs as the highest amount of events can be observed for this case. PSDs are using complete packets during their communications. Due to this reason their most important concern is their throughput like mobile devices. In this study we aggregated these two user types, mobile users and PSDs and called them as Throughput Concerned Devices (TCD). Both TBDs and TCDs can exist in one of the three states presented in Chapter 3. In Figure 4.2, we present nine IoT devices. In this figure it can also be seen that each device has a coverage range. This coverage range is defined as the area that the device can observe an event. Such an area definition may seem inappropriate as some devices, e.g. coffee machines, observes events that occurs within themselves. However, this definition is presented in the generalization phase and setting their coverage area equal to zero will state that this machine can only observe events within itself.

In chapter 2, a generic formula for the number of nodes (N) that needs to be active to observe P rate of the events is presented. While calculating N, the distribution of events was accepted as a uniform distribution. However, such an assumption that the events are distributing in the environment uniformly is an inaccurate assumption. It can also be extracted from the generic example of the businessman. The event of "hot coffee" can only be observed in certain places. A more generic example can

be the motion sensor case that can be modeled as an IoT device. Even though the motion seems to be a wide range event that can exist at any place at any time, detecting a human motion on a table is quite low. Due to this reason the usage of uniform probability function is not sufficient. A dynamic probability function should be applied to the system that changes the probability values according to the observed events. In the proposed probabilistic approach $P(C|x)$ is initially set to the previously calculated value, Eq.4.1. Based on this calculated N value the initial state of the network is set. During the working the network dynamically updates the necessary N value according to the encountered number of events by updating the probability function according to the presented equation in Eq.4.2.

$$N = \frac{P \times A}{\psi \times \pi \times R^2} \tag{4.1}$$

$$P = P + (P)^{\frac{1}{k}} \tag{4.2}$$

where k is the number of observed events. Such an update function also needs a regional approach. The wireless network area should be divided into n grids and the update process should be performed on these grids. For a more accurate approach, the equation 4.2 should be presented as in equation 4.3.

$$P = (P + n \times (-2 \times 1(k=0)+1) \times (P)^{\frac{1}{k}}) \times 1(-2 \times 1(k=0)+1) \times (P)^{\frac{1}{k}} \geq 0) \tag{4.3}$$

The function $1(x = m)$ returns 1 if $x = m$ and returns 0 if $x \neq m$. The grid size and the update frequency (f_{update}) are design parameters that affect the success of the framework. In our simulations we are using the random event distribution so it is not expected that the network controller will eventually reach a stable point as the event distribution is constantly changing. However, for a real life case, it is expected that the network will eventually will be reach a stable point.

4.4 The Self-Organizing Network Framework

Self-organizing network topology management framework pledges a powerful control mechanism to the network management framework that can dynamically change the network topology by changing the states of the base stations. However, the proposed frameworks so far needs a sacrifice in performance to increase the energy efficiency. Addition to this, they are all assuming that the expectations of the users are constant all

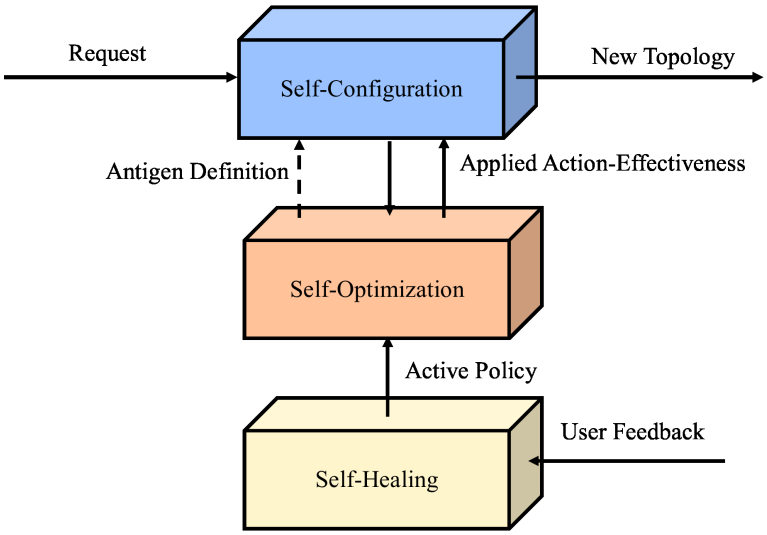


Figure 4.3: Proposed SON framework.

the time. However, our daily experiences shows that the network expectations change during the day as presented in Section 4.2. Addition to this wrong objective selection, the coexistence problem also became a major issue. In this study we are proposing a new network management framework that can;

- dynamically adjust its management policy according to the user expectations in daily bases,
- change its problem, antigen, definition according to the policy selection ,
- improve the presented configuration's quality using the Local Indicator of Spatial Association (LISA) coefficient.

The proposed system model is presented in Figure 4.3. We are defining the three attributes of the SON frameworks (i.e. self-configuration, self-optimization and self-healing) using some specifications of human immune system. Three possible policy is defined, Most Energy Efficient (MEE), Highest Performance (HP) and Balanced System (BaS).

Table 4.1: Policy objectives model.

	MEE	HP	BaS
Energy Consumption	Low	High	Static Limits
Performance	Low	High	Balanced

The performance and energy consumption objectives of different policies are presented in Table 4.1. MEE tries to minimize the energy consumption of the system by changing the network topology so that the network can operate in its optimum state. To decrease the energy consumption, like the previous study, we defined three possible actions that the network can use. These are *changing the user's connected base station*, *decreasing the base stations coverage area* and *turning the base station on/off*. These actions are the same as the ones presented in Chapter 2 so they will not be covered again. However, as there exist two different user types, instead of accepting a static action sequence, we define an action space that contains these three possible actions. The management framework can choose an action from this space. This selection mechanism does not cause any difference for mobile users but it is important for IoT devices, as actions like base station changing is not meaningful for these devices. HP policy demands highest possible QoS presentation to the user. In this work the considered performance metric of TCDs is their throughput and to increase it the acceptance ratio is increased. When the HP policy is selected the network tries to optimize the network by trying to accept as many users as possible. The topology change is performed without any consideration of the energy efficiency. The BaS policy is between HP and MEE. The energy consumption has a static limitation and if the power dissipation exceeds that limit then an action is performed to regain the optimal state. The main difference between BaS and MEE is the energy limit that triggers an action. BaS is more open to energy consumption than MEE.Active policy decision is a challenge rapidly rises in this study. In this study, for simplicity we only considered time as a trigger to change in the policy. The daytime is divided into three main parts and each of them is marked with different policies. In real cases there exist many cases that changes the network policy.

4.4.1 Proposed self-configuration framework

The proposed self-configuration framework consists of three main sub-blocks, i.e. *antigendetection*, *decision*, *memory management*, as shown in Figure 4.4. In this study, Small Cell Base Stations (SCBS) handle the most of the TCDs. The optimality of the network is maintained by optimizing the SCBSs performance that is defined according to the management policy. SCBCs receive the service requests from the

TCDs and maintain service to them. They are incapable of detecting any conflict between their current state and the management policy of the network. The state of a SCBS consists of the number of active users connected to this SCBS and the total energy dissipation of it. SCBSs transmit their states to the Main Base Station (MBS). The proposed framework is designed for MBSs. Addition to the states of SCBSs, the MBSs receive two other request types, one of which is the requests from TCDs that are not in the coverage area of a SCBS and directly connected to the MBS. The other kind of received signal is directly received from TBDs. TBDs transmits their state changes to the MBS and possible changes in the network topology is maintained. The control of the TBDs are similar to the *SoT* framework, however, the contribution of this study is performing all the network changes in a central place. This integrated control scheme enables the spread of different policies through the network more easily and also implementing learning frameworks to the network. All these three different

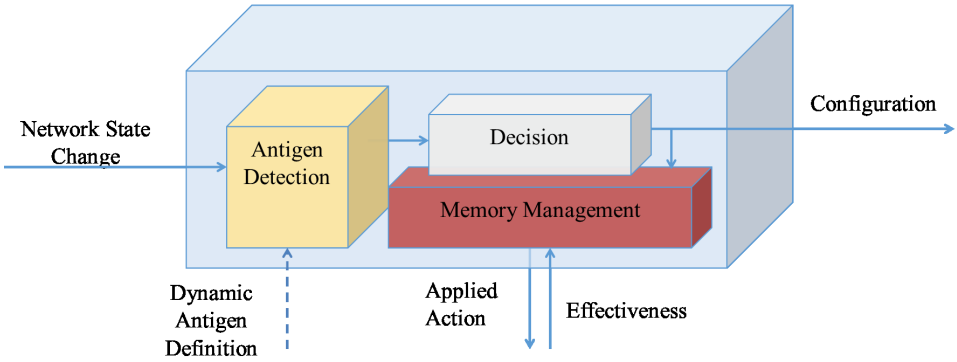


Figure 4.4: Total Covered Area per Energy change with TBD Traffic

kind of received signal is showed as "*request*" in Figure 4.4. This received request is first transmitted to the antigen detection block. Antigen detection block's first duty is to separate the messages from TBDs from other devices. TBD messages are directly transferred to the decision block. The remaining requests both coming from the SCBSs and TCDs are evaluated within the antigen detection block according to the active antigen definition.

The network topology should be optimized according to the active policy decision of the network management. In this study, the transitions between active policies are decided using the time of the day. The possible policies and their performance expectations are presented before. According to the policy the expected antigen definition is emitted from the self-optimization block. In this study to determine

the self-states and non-self-states, we used the previously used antigen determination equation, (4.4).

$$\zeta_i(t) = \frac{P_{tr,i}(t)}{N_i(t)} \tag{4.4}$$

We accept that the MBS cannot enter a non-self-state except for MEE policy. If the MEE policy is selected than the number of users connected to the MBS and the total power consumption of MBS to maintain the users communication are used to calculate the state of the MBS. If the MBS is in a non-self-state then the configuration and optimization processes are applied sequentially. For HP and BaS policies, the main exception is that the MBS can never enter a non-self-state so the determination of MBS's state is unnecessary. In Chapter 2, the non-self-states are determined by a threshold, δ_T. In this study, choosing different antigen levels for different policies performs the dynamic nature of antigen definition. It is obvious that the MEE policy should present the lowest threshold, $\delta_{T_{MEE}}$, while the HP policy presents the highest threshold, $\delta_{T_{HP}}$. The open form of (4.4) is also presented in (4.5).

$$\zeta_i(t) = \frac{\Sigma_{i=1}^{N} p \times (||L_{SCBS} - L_i||)^{\alpha}}{\lambda \times T_{average}}, \ \forall i \varepsilon N \tag{4.5}$$

If the state of the base station, $\zeta_i(t)$, is below the active antigen threshold, δ_{active}, then the base station is marked as a self-state and an acceptance is transmitted to the base station. However, if $\zeta_i(t)$ exceeds δ_{active}, then the base station is marked as a non-self-state and the configuration process is started.

As presented in Chapter 2, the network management topology actually decides amongst the three previously defined actions, namely user switching action, coverage area changing action and sleep mode action. The main studies about these actions are presented in Chapter 2, so they are not covered here again. The selection of the action is also performed using a probabilistic approach. The applied action and the detected problems are transmitted to the memory management block while applying these changes to the network. The memory management block consists of a long-term memory structure and a buffering block. The decision block transmits this applied action-problem couple to the buffering block. The buffering block transmits a copy of this couple to the self-optimization block and expects the result of this optimization process. The effectiveness message is received from the self-optimization block. This signal can be thought as the control input of a tri-state buffer. The effectiveness signal

can have two different value, *logic* 1 or *logic* 0. *Logic* 1 states that the applied action is optimum and can be transmitted to the long-term memory. However, the *logic* 0 implies that the action is not sufficient so it should be discarded. If the network controller detects the same antigen (the network state) in the antigen detection block, then it applies the previously saved action.

The self-configuration flow for TCD is similar to the one presented in Chapter 2. The TBD's self-configuration also follows the same flow presented in Chapter 3. This flow should be investigated under two main processes, the initialization process and the steady-state management process. The initialization process covers the settling up framework. All TBDs transmits their locations to the MBS. In the MBS, the antigen detection block passes these locations to the decision block. The decision block produces a vector containing all the devices and their states and passes this vector to the memory management block. The buffering block sends a copy of this vector to the self-optimization block, which returns the states of the devices (*active* or *passive*). Then this virtual map is loaded to the long-term memory. In the steady-state management process, the TBD network has a stable structure. During this situation, two kinds of network changes can exist. One is the setting up new TBDs and the other is the drained battery of the previously active TBDs. For these cases, again the memory management block transmits both the previous network topology and the change in the topology to the self-optimization block. This change in the network topology is applied to the previous network topology. If the change is the participation of a new TBD then it is added to the previous network topology vector as a new element with the active state. The optimization block again returns the latest version of the network topology to the memory management block. The buffering block is responsible for the loading of this new TBD network topology to the long-term memory. The changes from the previously network topology to the new topology is applied to the network.

4.4.2 Proposed self-optimization framework

The proposed self-optimization module consists of three main building blocks, which are learning framework block, policy objective control block and memory block. The self-optimization module has a crucial importance in this study for both TCDs and TBDs. For TBDs it decides the network topology, the states of the devices, to

achieve maximum lifetime with minimum energy consumption. Addition to this, in this study an event based device activation framework is applied, which implies that the event distribution within $2D$ space should be taken into consideration during the determination of the device states within the network. To achieve this, we applied a weighted event probability calculation during the calculation of necessary active devices and updated the number of number of necessary active devices, N, using the probability function presented in (4.3). This calculation is performed within learning framework block. This block can contain additional abilities like smart device management using knowledge extraction. More specifically, distinct attributes can be associated and using these connections more efficient decisions can be performed. However, a this study is more likely a premise study, this kind of smart device control systems are not covered. The second block, namely policy objective control block, is

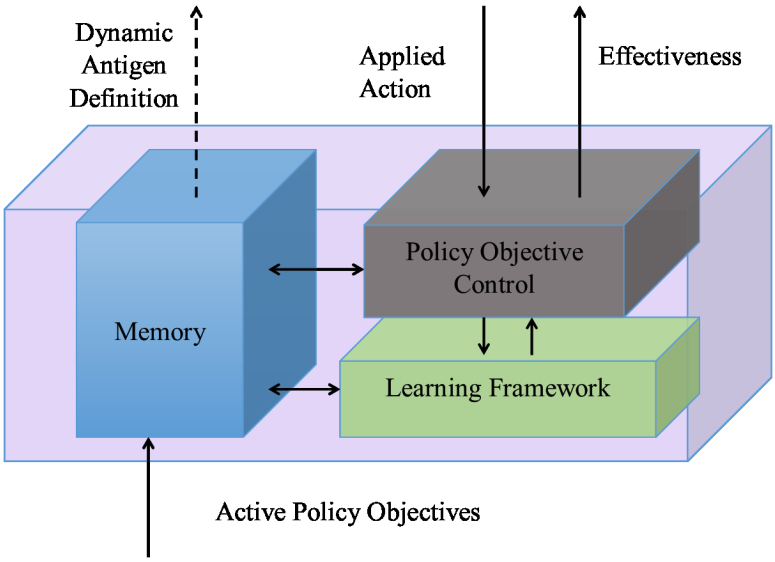


Figure 4.5: Total Covered Area per Energy change with TBD Traffic

where the network optimality control is performed. Its behaviors amongst the network situations can be investigated under two different cases.

For TBDs, it receives the network topology vector that contains all the live devices and their states. As mentioned earlier, a TBD can exist in three different states, active, passive and dead. TBDs in active or passive state are capable of communicating and have enough power to perform tasks. However, the dead TBDs do not have necessary power to perform any task. Due to this, only live (active or passive) TBDs are kept in the network topology vector. During the optimization phase, different network policies should trigger usage of different probability functions. More specifically, the

n coefficient should be changing according to the decided network policy. The applied n parameters according to the different network polies can be itemized as;

- for MEE policy $\rightarrow$ $n = 0.2$
- for BaS policy $\rightarrow$ $n = 0.4$
- for HP policy $\rightarrow$ $n = 0.6$

By changing the step size of the probability update function, the number of devices that should be activated for each period is determined. The activation process follows the sequence presented in Chapter 3. First using the conflict parameter the non-conflicted devices are activated. After that, using the Local Indicator of Spatial Association (LISA) coefficient the rest of the necessary devices are activated. This block returns the optimal TBD network topology vector to the self-configuration block.

For TCDs, the applied action-problem couple is received from the self-configuration block. The optimality of the applied action is measured in terms of the sequence of the applied action within the possible defined actions and whether the destruction of non-self-state of the base station. In Chapter 2, as only one policy is defined, MEE, the MBS can choose one of the three possible actions. However, in this structure there exist three possible policies with different performance metrics. Based on this fact, the selection of an action from the previously defined actions space is constrained in some case. More specifically, while the network is operating in HP policy, the sleep mode selection is not accepted as an active selection. Such couples should not be accepted and activated. Addition to this, like in Chapter 2, the sequence of the applied action is also crucial. Wrongly applied action sequences are rejected. Finally, the validity of the applied action (that passes both sequence check and policy check) is measured whether the applied action changes the base station's non-self-state or not. If it causes a state change, than this action-problem couple is accepted as a valid couple and then $logic$ 1 is transmitted to the self-configuration block that triggers the storage of this couple. In the future, if this problem is redetected, then this action can be performed.

Finally in memory block, two different works are performed, memorization of the n parameter and the antigen definition update. The used n parameter is kept in this discrete memory structure. By separating the self-configuration memory and self-optimization memory, the simultaneous reading and writing works are performed.

The most important duty of the memory block in self-optimization block is the antigen definition update process. In this study, as the static antigen a definition is applied, this block only performs a transmission of the existing data.

4.4.3 Proposed self-healing framework

The self-healing block is the part that is connected to the network manager. This feedback from the network manager or the users maintains an improved system structure. By this feedback mechanism, an improved version of topology management using knowledge extraction and artificial neural system based feature detection. However, this study only covers a premise work that is proposing an improvable version of SON deployment for hybrid user networks. Due to that, self-healing block in this study only decides the transitions between different policies. The proposed framework is presented in Figure 4.6. There exists two main blocks, policy decision block and policy objectives determination block. It is possible to argue that the

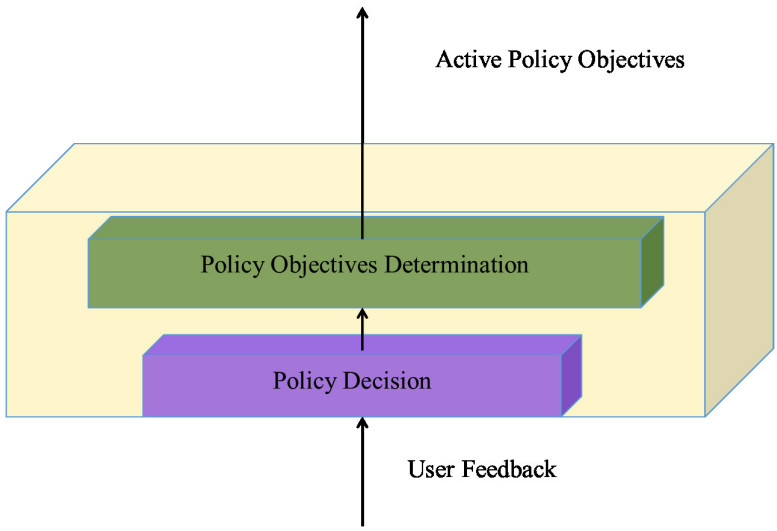


Figure 4.6: Total Covered Area per Energy change with TBD Traffic

determination of the policy and determination of its objectives are the equivalent arguments, which is also valid for this study. However, to maintain the generalizability attribute of this study, we divided these two concepts. As previously stated it is possible to implement some learning and knowledge extraction algorithms to the self-healing block. These extraction algorithms can choose specific objectives from an objective space. The effectiveness of the selected objective is evaluated from the user and is transmitted to the SON framework. Based on these evaluations, the extraction system

can update itself. This adaptive structure of the self-healing algorithm can make the network management system more adaptive and flexible while helping it to propose the most efficient actions and topologies without an actual human intervention. The first block, the policy decision, chooses the active policy according to the some attributes of the network, whereas, the second block, the policy objectives determination block, determines the most optimal objectives for the activated policy. However, as previously stated, this study is more likely a premise study that presents a successful management framework for hybrid networks. So this kind of additions (knowledge extraction or dynamic objective selection) is not covered in this study. Instead, we are using the specific objectives that are also presented in Table 4.1. These can be itemized as;

- For MEE policy, choose the action that minimizes the energy consumption.
- For HP policy, choose the action that increases the performance most.
- For BaS policy, choose the action that maintains the balance between energy and performance.

As previously stated, the specific attributes that trigger a state change can be selected dynamically or statically. Dynamical selection enables the network management topology to learn the specific attributes that effects the outcome expectations and enables the network management framework to adapt itself to the dynamic nature of the network. However, usage of these learning algorithms increases the complexity of the network. Static selection presents a more basic structure. However, this kind of a framework cannot adapt itself to the changeable nature of the network. In this study, the selection is performed statically with time variable. The time variable (t) and the applied polies are,

- $8\ am < t < 5\ pm \rightarrow HP$ policy
- $5\ pm < t < 2\ am \rightarrow BaS$ policy
- $2\ am < t < 8\ am \rightarrow MEE$ policy

The time variable is determined by the network manager feedback that is directly received to policy decision block. The objectives of the selected policy are transferred

to the self-optimization block. It is important that the policy knowledge is not passed to the self-optimization block.

4.5 Simulations

The proposed framework mainly proposes a hybrid structure that manages the system according to three different network policies (HP, MEE, BaS). In this section, we evaluated the performance of the system in terms of TCD's and TBD's performance metrics separately. The performed evaluations are repeated for different network policies and observed the results. We performed these simulations in MATLAB environment. The applied system parameters are presented in Table 4.2. For simplicity,

Table 4.2: Applied simulation parameters.

Number of MBSs	1
Number of SCBSs	10
$\delta_{T_{MEE}}$	3.5 $mW/User$
$\delta_{T_{HP}}$	7 $mW/User$
$\delta_{T_{BaS}}$	5 $mW/User$
P_1	0.5
P_2	0.4
P_3	0.1
A	200 m^2
R	2 m
N_{TBD}	60
$E_{TBD_{Battery}}$	50 W
E_{Sleep}	132 mW
E_{Idle}	554 mW
$E_{Receive}$	726 mW
$E_{Transmit}$	1089 mW

some assumptions are accepted during the simulations. First of all, all user devices are accepted to be immobile. Their locations do not depend time and constant through the simulations. Secondly, the TBD devices have a constant number and they are placed randomly at the beginning of the simulation. Nevertheless the numbers of TCDs are dynamically changing and they are randomly created and deleted during the simulations. The TCDs transmits requests with random bandwidth and service

time. Finally, we accepted that during the simulations only one request can received from each device type. More specifically, only one TCD can join to the network while only one TBD can observe an event.

4.5.1 Total energy consumption of the communication backhaul

The energy efficiency is one of the main concerns in this study. Due to this, we first investigated the overall energy consumptions through the network amongst different kind of devices, TBDs and TCDs. These two different kind of energy consumptions are separated from each other as energy efficiency is one of the performance metrics for TBDs whereas it is a secondary optimization parameter for TCDs. First the observed results for TCDs are presented in Figure 4.7. The energy consumption in the TCD backhaul is presented over three different policies for 100 hours of working in each policy. As previously stated, HP is the policy that tries to optimize the network topology so that the maximum performance can be received. Whereas, the MEE is the most energy efficient policy tries to minimize the energy consumption of the network. These specifications of different policies are visible in Figure 4.7. As expected,

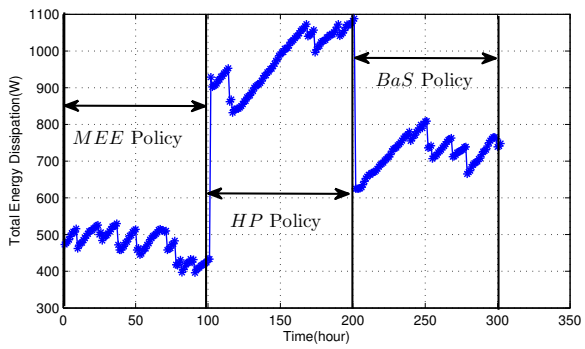


Figure 4.7: Total energy consumption in TCD backhaul.

the network is consuming more energy while it is operating in HP policy, whereas, it dissipates the minimum energy while it is working in MEE policy. One of the important results is the observed energy fluctuation in the network energy dissipation. For MEE policy, the average energy consumption is 480 mW. The maximum observed fluctuation has an amplitude of 70 mW. However, for HP policy, the average energy consumption is 980 mW. The observed amplitude of the energy oscillation is 120 mW which is nearly twice of MEE fluctuations. The BaS policy presents a steady work with an average of 720 mW and an amplitude of 80 mW. Comparing these results shows

that the average energy consumption and the maximum amplitude are effected by two concepts. The chosen threshold (δ_T) effects both of average energy consumption and fluctuations as it presents a range that the energy can oscillate. Another important concept that has a great impact on the energy fluctuations is the sleep mode action. In HP policy, the selection of sleep mode action is not accepted. Due to this reason the amplitude of fluctuations is increased. Such oscillations with high amplitude harms the electronic structures of the MBS and increases the OPEX.

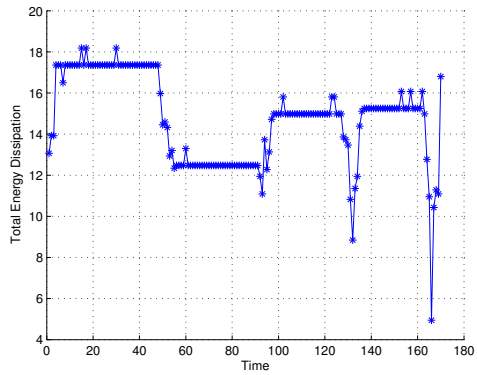
In Figure 4.8, the energy consumption of TBD network is presented. We divided the observation area into three subarea each one contains 60 devices. The main difference between these regions is the observed event rates. The number of devices is changed according to the observed number of events and the P parameter is updated. This update process is performed when the battery of a device is depleted. The changes in the number of events present three different management frameworks. For high event rate the device uses maximum energy to observe as much event as possible whereas for lowest case the devices presents an energy efficient network management framework that increases the durability of the network. It is obvious that such a weighted update process can increase the energy efficiency of the network. However, the passing from low event rate to high event rate is not very easy as such a transition needs a high amount of event observation within the environment. So such an update process is not very effective for dynamically changing environments.

4.5.2 Total acceptance ratio

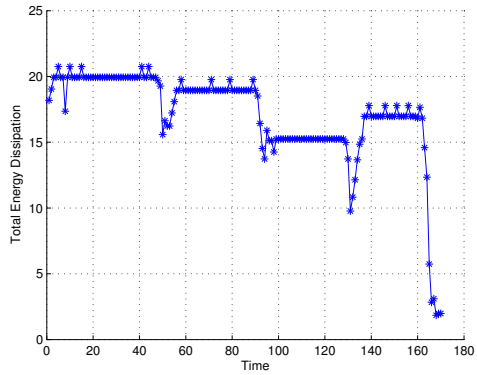
The acceptance ratio is the main performance metric of the TCDs. During the simulation to observe the effects of different network policies on acceptance ratio, we produced 150000 total requests (50000 for each policy) and calculated the accepted requests. Each request has a random time in the system, and a random bandwidth usage. The SCBSs handle the users until their states changes to non-self-state. MBS

Table 4.3: Acceptance rates per policy.

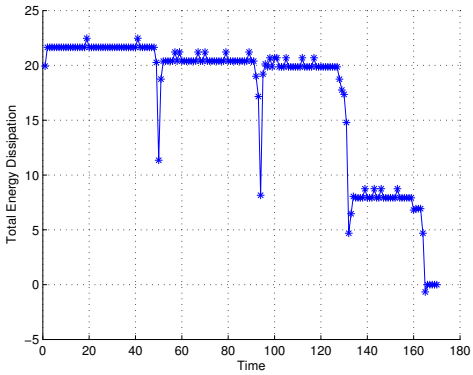
Policy:	MEE	HP	BaS
Acceptance Rate	0.8549	0.9269	0.8969
δ_T(Per SCBS)	3.5 $mW/User$	7 $mW/User$	5 $mW/User$



(a) Most Energy Efficient Policy



(b) Balanced System Policy



(c) Highest Performance Policy

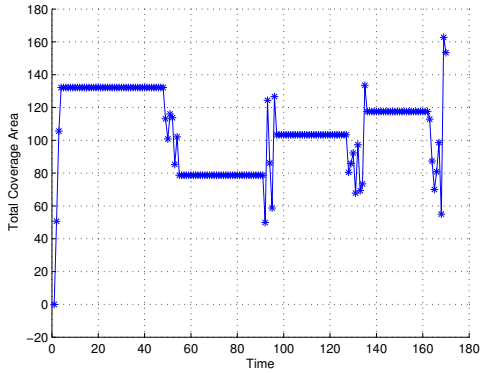
Figure 4.8: Total covered area per energy change with network policy

performs the previously explained actions in case of the detection of a non-self-state. The observed results are presented in Table 4.3.

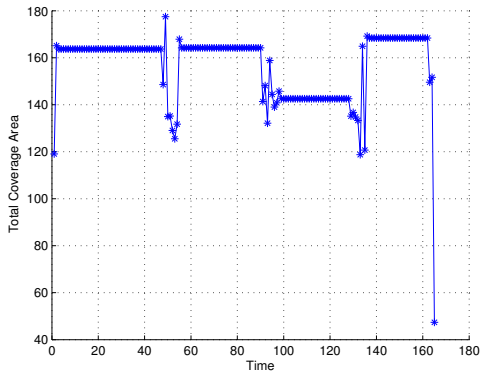
As expected, we observed that the acceptance rate receives its highest value for HP policy. This implies that the network handles 93% of the overall users even though they are not efficient. The MEE policy presents the lowest acceptance rate, 85%, which is a natural result of the energy optimization. We also observed the acceptance

rate of 90% for *BaS* policy which presents a midway working environment between HP and MEE. As there exist 50000 user requests and each user can send one request, this 8% of difference between acceptance ratios indicates that nearly 40000 user cannot receive service due to energy policy of the network management.

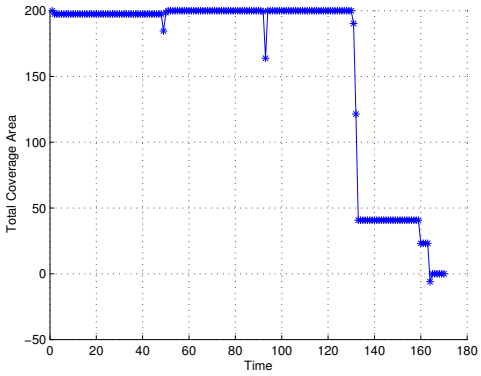
4.5.3 Performance evaluation on durability



(a) Most Energy Efficient Policy



(b) Balanced System Policy



(c) Highest Performance Policy

Figure 4.9: Total covered area per energy change with network policy

The durability is one of the performance metrics for TBDs. In this study, we observed the changes in the durability of the TBD network. As we used dynamic P parameters during our simulations, the determination of a borderline for the durability is not as obvious as it is in Chapter 3. Due to this reason, instead of using solid borderlines, we focused on the massive degradations on the coverage area. More specifically, if the coverage area decreases 60% from its previous state, we accept that its durability is ended. Because such a massive degradation cannot be explained with the degradation in P.

In Figure 4.9, the observed results are presented. It can be seen that for high event rates the network is getting an offline state by the 130th hour. For the remaining cases, low level and medium level event cases, the network still continues working by the end of 160th hour. If these results are combined with the energy dissipation results, it is obvious that dynamic P calculation methodology is not efficient for high event rate cases. However, for medium and low level event rates, such a dynamic framework improves the energy efficiency of the network and increases the durability of the network.

5. CONCLUSION AND FUTURE WORKS

In this study, the coexistence problem of heterogeneous user types and their effects on energy efficiency is investigated and a network management framework is proposed. The proposed framework contains two distinct structures, immune inspired green self-organizing network management structure and a self-organized things framework. These two distinct studies are integrated and an additional policy selection structure is implemented to this framework. As these two distinct frameworks are explained in separated sections, we are presenting their strengths and known weaknesses in discrete sections. Finally, we are presenting the unique specifications of the proposed framework and the expected future studies.

5.1 Strengths and Weaknesses of $I^2 - gSON$

In this study, we pointed the severity of the trade off between the performance of the network and the energy efficiency. We proposed a complete network management framework, $I^2 - gSON$ and inspiring from the immune system, we defined the three SON concept. The proposed B-cell inspired self-configuration framework changes the network topology and tries to optimize the network topology that maintains high performance while decreasing the energy consumption. The self-configuration block matches the performed action and problem couples and expects optimality information from the self-optimization block. This optimality control is mapped from the communication between the B-cell and the T-cell in immune system. This discrete activation framework optimizes the memory usage and maintains the storage of effective action-problem couples while the memory usage increases the speed of the action proposal. Finally, the self-healing framework enables the spread of network policies through the users. During the simulations we used a $1:10$ (1 MBS and 10 SCBSs) network topology and created 50000 random requests. The MBS tries to optimize the network in terms of energy efficiency. The proposed $I^2 - gSON$ framework is compared to the $SM - SON$ framework. During the simulations,

$I^2 - gSON$ presented a more stable and efficient energy usage. Moreover, we observed 26% increase in the acceptance ratio.

5.1.1 Strengths of the $I^2 - gSON$

The strengths of the proposed $I^2 - gSON$ framework can be listed as;

- The proposed $I^2 - gSON$ framework presents a simple and a generic modular structure that can be applied to the network management challenge. The network management polies can easily be imported to the network without actually affecting the stability of the network.
- The $I^2 - gSON$ framework presents an effective network topology management structure that can stabilize the energy efficiency while increasing the acceptance ratio.
- A strong memory management framework is mapped from the immune system. Inspiring from the B-cell division process in nature, the storage of action list and the activation process are proposed.
- The proposed network structure is better for dense network structures (e.g. city centers).

5.1.2 Weaknesses of the $I^2 - gSON$

The weaknesses of the proposed $I^2 - gSON$ framework can be listed as;

- The proposed framework can cause a pre-optimum solution oscillation problem. More specifically, the network topology may try to optimize the network with inefficient actions for a long time. The network management framework chooses the actions using a probabilistic selection process. This also implies that the network topology may choose the sleep mode action multiple times. Before choosing a previous action.
- The pre-optimum solution oscillation also decreases the speed of the network. The $I^2 - gSON$ performs the selected non-optimal actions, however, this non-optimal action selection decreases the performance of the network and decreases the QoS. Addition to this, the pre-optimum oscillation can also cause a fluctuation in the

energy usage, which can eventually lead to the aging problem, which will increase both CAPEX and OPEX.

- The complexity of $I^2 - gSON$ is higher then the $SM - SON$. It is not efficient for sparse network topologies.

5.2 Strengths and Weaknesses of *SOT*

With the development of cheep IC applications and spread of smart systems, a new user type is introduced to the network systems. The IoT devices, things, produce a huge amount of traffic with no solid QoS requirements. The only requirement of this user type is the self-management capability that may increase their lifetimes. However, for most of the cases, application of self-management algorithms only present a simple scheduling algorithm that decreases the performance of IoT network in terms of event observation. In this study, a green self-organized IoT framework, SoT, is presented that optimizes the energy consumption of the things and increases the lifetime of the network. We used conflict parameter and LISA coefficient to perform smart scheduling and increase the performance of the network. In the simulations, we first evaluate the success of the framework in terms of durability and coverage area per energy. We obtained 150% increase in durability and 220% increase in the overall lifetime. We also showed that our framework stabilizes the energy consumption by putting unnecessary devices into sleep mode. We used an energy efficient self-scheduling algorithm that sends unnecessary devices into sleep mode, if it is possible to cover the same area with lower number of devices. Finally the effects of traffic load are observed and seen that for different traffic loads, our framework guarantees the durability.

5.2.1 Strengths of the *SOT*

The strengths of the proposed framework can be itemized as;

- The proposed framework can perform 150% increase in durability and 220% increase in the overall lifetime of the network. This shows that this framework can maintain the energy efficiency demand of IoT devices.
- The proposed framework can perform the selection of remote TBDs, which increases the detection of distinct events. This algorithm depends on the idea

of continuous and discrete events. As continuous events like motion follows a sequence, the algorithm tries to increase the detection of discrete events.

5.2.2 Weaknesses of the *SOT*

The weaknesses of the proposed framework can be itemized as;

- The acceptance of normal event distribution is unpractical. In actual network topologies, detecting the same event in two distinct locations is not equal for most of the cases. For example, consider the event of the human motion. The probability of detecting this event at the door of an house is not equal to the detecting this event on table. So a more realistic probability distribution, like Gaussian distribution should be applied.
- Accepting a flat network topology in terms of IoT device type is a major assumption. Even though this assumption presents the selection of an efficient network topology, it presents a challenging task in the planning part, which is not covered in this study. The smart selection structure is going to be a complex framework, which may decrease the efficiency of the proposed framework. Note that as a future study, we are planning a local task management framework which can decrease the complexity of this planning structure.
- The proposed system uses an external controller, which is used in the initialization and healing parts. There exist an uncertainty of this controller and its role in the network management.

5.3 Strengths of The Proposed Framework

In the previous two sections, both strengths and the weaknesses of the preliminary studies are presented. The proposed framework, which is an integration of these two frameworks, contains the strengths of each of them. Additionally, it also solves some of the previous weaknesses. The unique strengths of this integrated framework can be listed as;

- A policy selection process is applied to the existing framework. Three possible frameworks, namely, Most Energy Efficient, High Performance and Balanced System.

- A simple and efficient SON framework is presented. The proposed framework can be used to handle different kind of users and with the implementation of specific blocks, it can perform greater tasks.
- Instead of a complete network space, the network is investigated under four different regions. The devices transmits their location knowledge at the initial state and the network management labels the user with a list marker. By this way, a better optimization process is performed.
- The calculation of the necessary device count to guarantee a generic event observation rate is updated. In the proposed framework, by using a uniform distribution the initial expected values of the number of devices is calculated. During the network configurations, based on the event observation rates the number of active devices is updated.

5.4 Future Works

In the following of this thesis, we are going to research the following open issues pointed out in the thesis;

- A more detailed model of the triggers that causes policy changes is going to be investigated. In this study, only one trigger, the time, is accepted, however, more detailed model help to reach a better optimum solution for the real case scenarios.
- A knowledge extraction model is going to be applied to the self-optimization and self-healing blocks. By this model, the network management can dynamically produce valid assumptions that help the production of new topologies that can decrease the energy.
- A hidden layered markov chain based auto-reducing framework is going to be applied to the self-optimization mechanism that can dynamically adjust the antigen attributes that are not valid for specific networks.
- Larger antigen space and a larger action space is going to be implemented.
- The effects of the mobility of the users are going to be investigated.

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