

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**RESOURCE MANAGEMENT OF NETWORKED PHASED ARRAY
AIR DEFENSE SYSTEM RADARS**

Ph.D. THESIS

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Electronics and Communications Engineering Department

Electronics Engineering Programme

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**AĞ TABANLI FAZ DİZİLİ HAVA SAVUNMA
SİSTEM RADARLARININ KAYNAK YÖNETİMİ**

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To my family,



FOREWORD

The work presented in this thesis was conducted during my Ph.D. study at Electronics Engineering Programme of Electronics and Communication Engineering Department in Istanbul Technical University Graduate School. First of all, I would like to express my respect and gratitude to my advisor, Prof. Dr. Hakan Ali ÇIRPAN, for his support, encouragement and guidance. He kept me motivated all the time throughout the whole thesis period in order to overcome the difficulties that I faced during my PhD study. Secondly, I would like to thank ASELSAN for providing me all the opportunities throughout the whole period. I also want to take this opportunity to acknowledge all the people who believed and supported me. Last, but not least, I would like to express my endless gratitude to my family for the support and understanding they have shown when it was most required.

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ABBREVIATIONS

ADS	: Air Defense System
AHP	: Analytical Hierarchy Process
AI	: Artificial Intelligence
ANP	: Analytical Network Process
BCRLB	: Bayesian Cramér–Rao Lower Bound
BFIM	: Bayesian Fisher Information Matrix
CA	: Constant Acceleration
CPA	: Closest Point of Approach
CPT	: Conditional Probability Table
CT	: Constant Turn
CV	: Constant Velocity
DA	: Defended Asset
DB	: Data Base
DP	: Dynamic Programming
DSS	: Decision Support System
EKF	: Extended Kalman Filter
FCC	: Fire Control Center
FCR	: Fire Control Radar
FRBS	: Fuzzy Rule-Based System
GA	: Genetic Algorithm
GBAD	: Ground Based Air Defense System
GFS	: Genetic Fuzzy System
GFT	: Genetic Fuzzy Tree
GNN	: Global Nearest Neighbour
IMM	: Interacting Multiple Model
JPDA	: Joint Probabilistic Data Association
KB	: Knowledge Base
KF	: Kalman Filter
LPI	: Low Probability of Intercept
MF	: Membership Function
MHS	: Multiple Hypothesis Tracking
MI	: Mutual Information
MIMO	: Multiple Input Multiple Output
MLS	: Missile Launching System
MPAR	: Multifunction Phased Array Radar
MSE	: Mean Square Error
PDA	: Probabilistic Data Association
QoS	: Quality of Service
RB	: Rule Base
RMSE	: Root Mean Square Error

RRM	: Radar Resource Manager
SM	: Sensor Management
SNR	: Signal-to-noise Ratio
TADMUS	: Tactical Decision Making Under Stress
TE	: Threat Evaluation
TOPSIS	: Technique for Order Preference by Similarity to Ideal
TQ	: Track Quality



SYMBOLS

$\mathbf{Y}_k$	: k_{th} detection
$\bar{\mathbf{Y}}_k$	: Unassociated k_{th} detection
$\hat{\mathbf{x}}(k k)$	: State vector at time-step k
$\hat{\mathbf{x}}(k k-1)$	: State vector at time-step $k-1$
$\mathbf{H}_x$	: Linearized measurement matrix
$\mathbf{T}_k$	: k_{th} track
$\mathbf{H}_x$	: Linearized measurement matrix
$\mathbf{K}$	: Kalman gain
$\mathbf{P}$	: State estimation covariance matrix
$\mathbf{R}$	: Measurement noise covariance matrix
f_c	: Fitness function
$\hat{\mu}^j$	: Updated model probability
$\mathbf{Z}^j(k)$	: Innovations
$\tilde{\mathbf{S}}^j(k)$	: Innovation covariance matrix
$\hat{\mu}^j$	: Updated model probability
c	: Normalization constant
$\hat{\mu}_i^{CT}$	: Constant turn model probability
$\mathbf{X}_k^q$	: State vector of the q th target at the time instant k
$\mathbf{F}^q$	: Transition matrix for q th target at k th time frame
$\mathbf{W}_{k-1}^q$	: Additive Gaussian noise for q th target at $k-1$ th time frame
$\mathbf{Q}_{k-1}^q$	: Covariance
$\mathbf{I}_2$	: Order 2 identity matrix
$\mathbf{z}_{i,k}^q$	: Measurement for radar node i at the time instant k for target q
$\mathbf{h}_i(\mathbf{X}_k^q)$	: Measurement function
$\mathbf{v}_{i,k}^q$	: Noise measurement vector



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RESOURCE MANAGEMENT OF NETWORKED PHASED ARRAY AIR DEFENSE SYSTEM RADARS

SUMMARY

Air dominance plays a crucial role in today's battlefield, and its importance has increased over time with the development of advanced platforms and commercial technologies that enable the proliferation of air and missile threats. The importance of ground-based air defense systems, which protect air space and critical infrastructure, is also increasing in line with the development of those threats. The performance of air defense systems depends not only on the interceptor's performance or the capacity of the radar used to track targets but also on how efficiently those interceptor or radar resources are utilized during engagement operations. It has come to a point where increasing the performance of individual systems is inadequate, and networking of those air defense systems is needed to further improve the overall effectiveness of air defense operations by sharing radar and interceptor resources between them.

Modern air and missile defense systems utilize multifunction phased array radars as their primary sensors. These radars perform various system functions such as surveillance, tracking, and fire control simultaneously with the help of agility provided by the electronic beam steering. However, each function utilizes radar resources, requiring them to be coordinated according to their added value to overall mission effectiveness. The tasks allocated to each radar function are coordinated by a radar resource manager, which is a critical component of the overall performance of each radar. When multiple air defense systems with long-range radars are utilized in a region of interest, the coverage of those systems' radars overlaps, leading to overutilizing radar resources for the targets within this overlap region. These systems can be networked together to manage radar resources collectively. This networking beat a path to the concept of networked radar resource management with several benefits, such as tracking highly maneuverable targets, increased firepower due to efficient usage of resources, increased counter-countermeasures, and low-observability of air defense systems by shared tracking, thus increasing overall air defense mission effectiveness.

In this thesis, we propose radar resource management algorithms for networked phased array air defense system radars, which mainly utilize target priority for radar resource allocation. The main reason for using target priority for radar resource allocation is that the weapon allocation process primarily relies on the priority of the target in an air defense system. Among the various methods for determining target priority, fuzzy rule-based systems stand out due to their ease of adaptation by adding or changing rules and their ability to reflect expert knowledge. We first propose a novel adaptive fuzzy rule-based threat evaluation system based on genetic fuzzy systems, which learns the threat evaluation system model from a survey applied to air defense experts, allowing

real-time operator input to tune the threat evaluation decision support system. The real-time nature of this system ensures that the radar resource manager to be adjusted on the fly, responding to changing threat conditions and mission requirements. The proposed method allows full automation of fuzzy logic rule generation through a survey applied to air defense experts and near real-time tuning of the fuzzy rule-based system during air defense system operation. Apart from the previous work, this study utilizes genetic fuzzy systems to automate fuzzy rule-based system components during training and in the context-dependent operational mode.

Secondly, we propose a novel networked radar resource management algorithm based on an adaptive target-tracking technique. Multifunction phased array radars allow adaptive update rate of the target via beam agility provided by the electronic steering. This capability enables targets to be tracked more often on the maneuvering portion of their flight and less often during their straight flight paths. Also, target priority can be used to track threatening high-priority targets more frequently than the ones with less priority, such as distant or friendly targets. An extension of adaptive tracking to networked radars is possible where target update tasks are shared between radar nodes in the network. We proposed a networked radar resource management algorithm that utilizes target priority and target maneuver to adaptively track targets to manage radar resources of the air defense network. The results of this algorithm have been tested for different target numbers in multiple target scenarios, and simulation results have shown that the tracking and search resources between the radars in the network are effectively shared among each other in saturation situations that push the radar tracking limits. The differences between the situation in which there was no resource sharing and the situation in which resource sharing was made were compared based on the changes in the track initiation time and the changes in the frame time. As a result, it has been observed that adaptive tracking based on target priority and maneuver in network-based radars provides effective resource sharing between radars in the network and shortens track initiation times and frame times which eventually improves air defense effectiveness.

The final objective of the thesis is to develop resource management algorithms for networked air defense radars based on optimization techniques. Optimization approaches in radar resource management vary from using optimization objectives such as achieving required tracking accuracy, minimizing power allocation, limiting bandwidth, optimum dwell allocation, etc. Studies have also been conducted using a combination of two or more objectives simultaneously. Researches focusing on the resource allocation of a single radar have recently found frequent applications to radar networks. Since air defense systems utilize interceptors whose performance is guaranteed for required tracking accuracies, tracking accuracy is selected as the primary optimization parameter for networked radars in an air defense system. An optimization strategy is utilized to choose the minimum number of tracking radars to minimize the cost function formed by tracking quality metrics related to threat priorities and the Bayesian Cramér–Rao Lower Bound. The effectiveness of the proposed algorithm, which dynamically selects target tracking quality and minimizes tracking resources in an ADS by utilizing surrogate optimization suitable for real-time implementation, has been shown using simulations in an operational saturation attack scenario. As a second case study, the optimization constraints are extended with the total transmit power limitation and of the networked radars under tracking capacity limitation. This objective is crucial, especially when reducing the observability of

the air defense radars against threats with advanced electronic warfare capabilities is required. The result of the proposed algorithm is compared with networked radars operating with and without power optimization objectives and shown to provide required tracking accuracy requirements with the least possible power output.

In summary, this thesis explores novel radar resource management algorithms for networked phased array air defense system radars. We propose various threat priority-based networked radar resource management algorithms that can be utilized in air defense networks. A networked shared adaptive tracking algorithm that utilizes target priority and maneuvers to share radar resources while satisfying the tracking requirements for high-priority targets to be engaged is proposed. Algorithms for target priority-based optimization of radar resources have been developed under target tracking requirements and transmit power limitation constraints to increase the survivability of air defense systems. In addition, a novel adaptive fuzzy rule-based threat evaluation system based on genetic fuzzy systems has also been developed to adapt itself to the operational scenario and real-time operator inputs. This system can be incorporated into developed networked radar resource management algorithms that rely on threat priority as its main optimization objective.



AĞ TABANLI FAZ DİZİLİ HAVA SAVUNMA SİSTEM RADARLARININ KAYNAK YÖNETİMİ

ÖZET

Günümüz muharebe sahasında hava hakimiyeti hayati bir rol oynamakta olup, hava tehditlerinin çoğalmasını sağlayan gelişmiş platformların ve ticari teknolojilerin gelişmesiyle birlikte önemi zaman içinde daha da artmıştır. Hava tehditlerinin gelişmesine paralel olarak hava sahasını ve kritik altyapıyı koruyan kara konuşlu hava savunma sistemlerinin önemi de artmaktadır. Hava savunma sistemlerinin performansı, yalnızca önleyicinin performansına veya hedefleri izlemek için kullanılan radarın kapasitesine değil, aynı zamanda bu önleyicinin veya radar kaynaklarının angajman operasyonları sırasında ne kadar verimli kullanıldığına da bağlıdır. Günümüz harekât ortamında tekil sistemlerin performansının artırılmasının yetersiz kaldığı bir noktaya gelinmiş olup, hava savunma operasyonlarının genel etkinliğinin daha da artırılması için ağ tabanlı hava ve füze savunma sistemleri arasında radar ve önleyici kaynaklarının paylaşılmasına ihtiyaç duyulmaktadır.

Modern hava ve füze savunma sistemleri, sensor olarak çok işlevli faz dizili radarları kullanır. Bu radarlar, elektronik yönlendirmenin sağladığı huzme çevikliği sayesinde gözetleme, takip ve atış kontrolü gibi çeşitli sistem fonksiyonlarını aynı anda yerine getirmektedir. Bununla birlikte, her işlev radar kaynaklarını kullanır ve bunların genel görev etkinliğine katma değerlerine göre koordine edilmelerini gerektirir. Her bir radar fonksiyonuna tahsis edilen görevler, her bir radarın genel performansının kritik bir bileşeni olan bir radar kaynak yöneticisi tarafından koordine edilmektedir. Hava savunma etkinliğinin artırılması maksadıyla ilgi duyulan bir bölgede uzun menzilli radarlara sahip birden fazla hava savunma sistemi kullanıldığında, bu sistemlerin radarlarının kapsama alanı örtüşmekte ve bu örtüşme bölgesindeki tehditler için radar kaynaklarının gereğinden fazla kullanılmasına yol açmaktadır. Bu sistemler, örtüşen alanlardaki radar kaynaklarını birlikte yönetmek için bir ağ oluşturabilir. Oluşturulan bu ağ, yüksek manevra kabiliyetine sahip hedeflerin izlenmesi, kaynakların verimli kullanımı nedeniyle artan ateş gücü sağlanması, artan karşı önlemler ve ortak izleme yoluyla hava savunma sistemlerinin düşük tespit edilebilirliğinin sağlanması gibi çeşitli faydalarla ağ bağlantılı radar kaynak yönetimi kavramına öncülük eder ve böylece hava savunma görevinin etkinliği genel olarak artar.

Bu tezde, radar kaynak tahsisi için esas olarak hedef önceliğini kullanan, ağ bağlantılı faz dizili hava savunma sistemi radarları için radar kaynak yönetimi algoritmaları çalışılmıştır. Radar kaynak tahsisinde hedef önceliğinin kullanılmasının temel nedeni, hava savunma sisteminde silah tahsis sürecinin esas olarak hedefin önceliğine dayanmasıdır. Hedef önceliğinin belirlenmesine yönelik çeşitli yöntemler

arasında bulanık kural tabanlı sistemler, kuralların eklenmesi veya değiştirilmesi yoluyla uyarlanma kolaylığı ve uzman bilgisini yansıtmaya yetenekleri nedeniyle öne çıkmaktadır. Tezde ilk olarak, tehdit değerlendirme sistem modelini hava savunma uzmanlarına uygulanan bir anketten öğrenen ve tehdit değerlendirme karar destek sistemini ayarlamak için gerçek zamanlı operatör girdisine olanak tanıyan, genetik bulanık sistemlere dayalı yeni bir uyarlanabilir bulanık kural tabanlı tehdit değerlendirme sistemi önerilmektedir. Bu sistemin gerçek zamanlı yapısı, radar kaynak yönetiminin değişen tehdit koşullarına ve görev gereksinimlerine yanıt verecek şekilde anında ayarlanabilmesini sağlar. Önerilen yöntem, hava savunma uzmanlarına uygulanan bir anket ve hava savunma sistemlerinin operasyonu sırasında bulanık kural tabanlı sistemin gerçek zamanlıya yakın ayarlanması yoluyla bulanık mantık kural üretiminin tam otomasyonuna olanak tanır. Önceki çalışmanın yanı sıra, bu çalışma, eğitim sırasında ve bağlama bağlı operasyonel modda bulanık kural tabanlı sistem bileşenlerini otomatikleştirmek için genetik bulanık sistemlerden yararlanmaktadır. Önerilen sistem, ağ tabanlı ve bulanık mantık tabanlı tehdit önceliğine dayalı kaynak yönetim algoritmalarında tehdit önceliğinin zaman içerisinde kendi kendini uyarlamasına ve değişen tehdit ortamına adapte olmasını sağlamasına imkân tanıyacaktır.

İkinci olarak, uyarlanabilir bir hedef izleme tekniğine dayanan yeni bir ağ bağlantılı radar kaynak yönetimi algoritması önerilmektedir. Çok işlevli faz dizili radarlar, elektronik yönlendirmenin sağladığı huzme çevikliği yoluyla hedefin uyarlanabilir takip güncelleme hızına olanak tanır. Bu yetenek, hedeflerin uçuşlarının manevra yaptıkları kısımda daha sık ve düz uçuş yolları sırasında daha az sıklıkla takip edilmesine olanak tanır. Ayrıca hedef önceliği, tehditkâr yüksek öncelikli hedefleri, uzak veya dost hedefler gibi daha az önceliğe sahip olanlardan daha sık takip etmek için kullanılabilir. Hedef güncelleme görevlerinin ağdaki radar düğümleri arasında paylaşıldığı durumlarda, uyarlanabilir izlemenin ağ bağlantılı radarlara genişletilmesi mümkündür. Hava savunma ağının radar kaynaklarını yönetmek amacıyla hedefleri uyarlanabilir bir şekilde takip etmek için hedef önceliğini ve hedef manevrasını kullanan, ağ bağlantılı bir radar kaynak yönetimi algoritması önerilmiştir. Bu algoritma sonuçları çoklu hedef senaryolarında farklı hedef sayıları için test edilmiş, radar takip limitlerini zorlayan doyum durumlarında ağda bulunan radarlar arasındaki takip ve arama kaynaklarının etkin bir şekilde birbirleri arasında paylaşıldığı simülasyon sonuçları ile gösterilmiştir. Herhangi bir kaynak paylaşımının yapılmadığı durum ile kaynak paylaşımının yapıldığı durum arasındaki farklar iz başlatma süresindeki değişimler ve pencere zamanındaki değişimler üzerinden karşılaştırılmıştır. Sonuç olarak, ağ tabanlı radarlarda hedef önceliğine ve manevraya dayalı uyarlanabilir izlemenin ağda bulunan radarlar arasında etkin kaynak paylaşımını sağladığı, iz başlatma sürelerini ve pencere zamanlarını kısalttığı ve böylelikle hava savunma etkinliğinin artırılmasına katkı sağladığı görülmüştür.

Tezin nihai amacı, ağ bağlantılı hava savunma radarları için optimizasyon tekniklerine dayalı kaynak yönetimi algoritmaları geliştirmektir. Radar kaynak yönetiminde optimizasyon yaklaşımları, gerekli izleme doğruluğunun elde edilmesi, güç tahsisinin en aza indirilmesi, bant genişliğinin sınırlandırılması, optimum bekleme tahsisi gibi optimizasyon hedeflerinin kullanılması açısından farklılık gösterir. Ayrıca iki veya daha fazla hedefin aynı anda bir kombinasyonu kullanılarak yürütülen optimizasyon çalışmaları da yürütülmüştür. Tek bir radarın kaynak tahsisi üzerine yoğunlaşan çalışmalar ve son dönemde radar ağlarına da sıklıkla uygulama alanı

bulmuştur. Hava savunma sistemleri, gerekli izleme doğruluğu için performansı garanti edilen önleyicileri kullandığından, bir hava savunma sistemindeki ağ bağlantılı radarlar için izleme doğruluğu birincil optimizasyon parametresi olarak seçilmiştir. Tehdit öncelikleri ve Bayesian Cramér-Rao Alt Sınırı ile ilgili kalite ölçümlerinin izlenmesiyle oluşturulan maliyet fonksiyonunu en aza indirmek amacıyla en az sayıda izleme radarını seçmek için bir optimizasyon stratejisi kullanılır. Hedef izleme kalitesini dinamik olarak seçen ve gerçek zamanlı uygulamaya uygun vekil optimizasyon kullanarak hava savunma sistemindeki izleme kaynaklarını en aza indiren önerilen algoritmanın etkinliği, operasyonel doygunluk saldırısı senaryosunda simülasyonlar yapılarak gösterilmiştir. İkinci bir vaka çalışması olarak optimizasyon hedefi, ağ bağlantılı radarların toplam gönderme gücü sınırlamasıyla genişletilmiştir. Bu hedef, özellikle gelişmiş elektronik harp kabiliyetlerine sahip tehditlere karşı hava savunma radarlarının gözlemlenebilirliğinin azaltılması gerektiğinde hayati önem taşımaktadır. Önerilen algoritmanın çıktıları, güç optimizasyonu hedefleri olarak ve olmadan çalışan radarlarla karşılaştırılmış ve atış kontrol hassasiyeti için gerekli izleme doğruluğu gereksinimlerinin mümkün olan en az güç çıkışıyla sağlandığı gösterilmiştir.

Özetle, bu tezde ağ bağlantılı faz dizili hava savunma sistemi radarları için yeni radar kaynak yönetimi algoritmaları geliştirilmiştir. Hava savunma ağlarında kullanılabilecek tehdit önceliğine dayalı ağ tabanlı radar kaynak yönetimi algoritmaları önerilmektedir. Uyarlanabilir hedef izleme tekniği sayesinde manevra yapan yüksek öncelikli hedeflerin ağda bulunan radarlar arasında kaynak paylaşımını en iyileyecek şekilde daha sık izlenmesini sağlayan algoritma aynı zamanda hedefin imhası için kullanılacak önleyicinin ihtiyaç duyduğu takip doğruluğunun sağlanmasını da mümkün kılmaktadır. Buna ek olarak, hedef önceliğine dayalı, istenilen takip doğruluğunu sağlayacak şekilde ağda bulunan radarların en etkin şekilde seçilmesine imkân tanıyan ve gerçek zamanlı uygulamalara yönelik kullanım alanı bulunan optimizasyon tabanlı radar kaynak yönetim algoritması geliştirilmiştir. Bu algoritma hava savunma sistemlerinin beka kabiliyetini artırmak için hedef izleme gereksinimleri ve gönderme gücü sınırlama kısıtlamaları altında radar kaynaklarının hedef önceliğine dayalı optimizasyonuna yönelik geliştirilmiştir. Bu yapılan çalışmalara ek olarak, bu tez kapsamında kendisini operasyonel senaryoya ve gerçek zamanlı operatör girdilerine adapte edecek şekilde genetik bulanık sistemlere dayalı yeni bir uyarlanabilir bulanık kural tabanlı tehdit değerlendirme sistemi de geliştirilmiştir. Bu sistem, ana optimizasyon hedefi olarak tehdit önceliğine dayanan gelişmiş ağ bağlantılı radar kaynak yönetimi algoritmalarının da kullanıldığı ağ tabanlı hava savunma sistemleri içerisinde hedef önceliği kurallarının sisteme otomatik olarak tanıtılması ve zaman içerisinde değişen operasyonel koşullara göre kendi kendisini uyarlaması amacıyla kullanılabilecektir.



1. INTRODUCTION

The proliferation of technologies and decrease in the cost of weapons have led to an increased number of threats to be utilized to overwhelm the defence capability of current air defence systems (ADSs). The increase in the number of threats leads to a decrease in system performance figures such as detection range, total number of targets to be tracked, and tracking quality. To restore air defence capability hampered by the increasing number of mixed-type threats, multiple air defence systems should be deployed to regions where a high level of protection is required for critical assets such as military bases, industrial centers, etc. Additionally, for mutual protection, radar coverage of those systems is overlapped in the defense zone that is aligned with the most probable threat approach routes.

Modern air and missile defense systems employ Multifunction Phased Array Radar (MPAR), providing multiple radar functions such as search, track, fire control support, and communications in a single system. The flexibility provided by beam pointing agility and adaptability of the various radar parameters, such as waveform and output energy, provides this multi-functional capability. However, a radar resource manager (RRM) should be utilized to share radar resources amongst different radar functions. In an MPAR, RRM has a critical role in maximizing performance by controlling radar parameters to optimize radar time and energy budget according to a cost function that is determined as part of a single radar or an overall mission of a system in which the radar operates.

When multiple ADSs utilizing MPAR are deployed to a region to restore air defense effectiveness, they spend the same amount of resources on the targets that are within the overlapped coverage region. These systems shall be networked together in a cooperative way to enable the sharing of radar resources, which leads to the concept of RRM for networked radars. The benefits of this cooperation may be summarized to provide mutual support on tracking highly maneuverable targets,

increased counter-countermeasures, low observability of the defense systems, and increased firepower resulting from the efficient use of radar resources [1].

In light of these assessments, there is an increasing need for efficient RRM techniques to be utilized for networked radars, which are also applicable to networked ADSs utilizing MPAR. In this thesis, resource management algorithms are proposed for networked phased ADS radars to increase the overall defense effectiveness against the current and future threat environment.

1.1 Purpose of Thesis

The performance of the MPAR of an ADS is an important contributor to the overall defense effectiveness since it provides key functions of detection, tracking, and weapon support, as well as fire control functions such as kill assessment. An increased number of threats leads to a decrease in the key performance metrics such as tracking quality, detection time, track initiation time, and total number of simultaneously tracked targets. The decreased performance metrics should be improved by sharing the abundant radar resources of the network to restore or even improve the system of system performance.

The main motivation of this thesis is to explore novel RRM techniques for multifunction fire control radars of the networked air and missile defense systems to increase the overall air defense effectiveness. Since the problem domain is not dedicated to individual radar resource management, the focus will be to explore macro-level RRM techniques for networked ADSs. These RRM techniques approach the problem domain from the air defense mission objectives down to management at the networked radar level. The advantages of the developed RRM techniques are shown using simulations, and improvement of key air defense performance metrics are shown to represent their effectiveness.

We hope that the RRM techniques developed in this thesis will help to increase the effectiveness of National Air and Missile Defense Systems when operated together on the battlefield. Although it is an active research topic in the world academic community, when the national thesis database is examined, it is seen that there is no thesis topic related to networked radar resource management. We believe that this

thesis will also motivate the researchers in Turkey to conduct additional research on the active subject of networked radar resource management.

1.2 Literature Review

Research on RRM of networked radars has attracted attention in recent years, with the intent to find solutions to the increasing threat environment. RRM techniques are a subject that can be categorized under the general sensor management problem. Sensor management (SM) is a general term to describe the methods used to optimize the sensing sources' overall performance to fulfill the user's mission objectives. SM is defined as control of the degrees of freedom in an agile sensor system to satisfy operational constraints and objectives [2]. The objective has been stated as selecting the right sensor to perform the right service on the right object at the right time [3]. SM has many advantages, including reducing the operator's workload, optimizing the sensor mix, efficiently using different characteristics of the sensors, and effectively using limited system resources. The sensor management acts like a feedback controller from various system functions, such as the operator, fire control, situation assessment, data association, and the sensor itself, as shown in Figure 1.1.

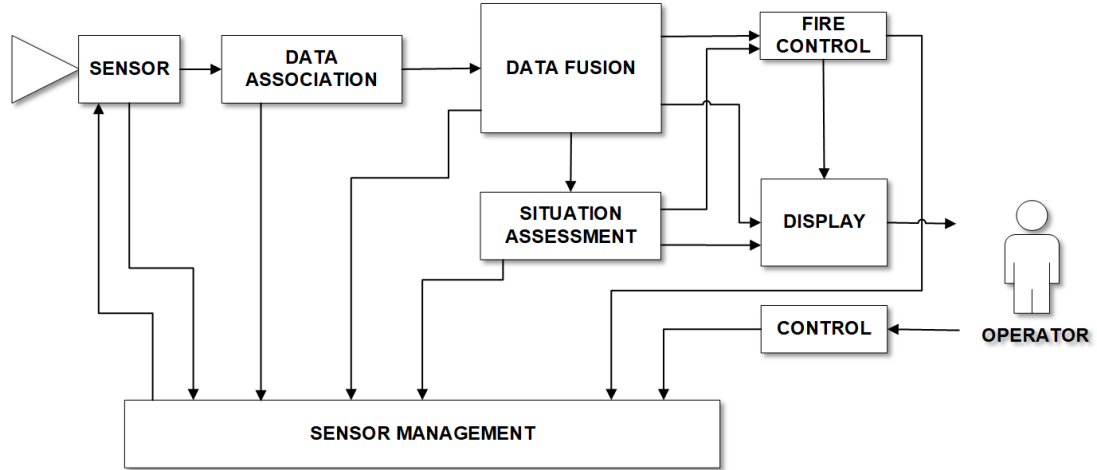


Figure 1.1 : Sensor management as a feedback controller.

SM has been categorized into three levels; the first level is named low-level control, in which frequency and direction of the sensor are controlled; the second level is named medium-level control, in which sensor modes are managed; and the third level is named sensor high-level process which deals with sensor to sensor interaction [4]. SM

techniques fall into two main categories: scheduling and decision-making. Scheduling aims to realize the execution of sensor tasks, while decision-making tries to find which sensor task shall be prioritized to execute. Decision-making approaches fall into two categories consisting of normative and descriptive techniques. The normative approach relies on an axiomatic description of human decision-making and specific a priori collected data relevant to the decision. The benefit of this approach is it allows a system design for which performance criteria can be analyzed, and its performance is guaranteed with respect to a defensible criterion. On the other hand, the descriptive technique tries to mimic human decision-making with the available information. SM combines descriptive and normative information in a descriptive system framework, which is driven by the situation assessment [5].

There are three important aspects to implementing an SM system. These are defining the architecture, selecting the scheduling technique, and selecting the decision-making technique to be used. The SM architecture is divided into two components: a Macro Sensor Manager and a Micro Sensor Manager. The Macro Sensor Manager deals with “What tasks need to be accomplished?” and the Micro Sensor Manager deals with “How should tasks be accomplished?” according to the task given by the macro manager. The possible deployment of the Macro Sensor Manager is where the fusion center and the situation assessment block will reside, and the possible deployment for the micro-manager is within the radar itself. According to the role of the situation assessment, it may be thought to be part of the data association and data fusion box or a part of the macro sensor manager.

Scheduling, which is a Micro Sensor Manager operation, can be categorized into two main approaches. The "best first" approach is also named the "myopic" approach, and the "brick packing" approach is also named as the "local optimum" [5].

The "best first" approach shown in Figure 1.3 allows rescheduling of the failed tasks within the time period and also allows pop-up tasks to be scheduled as soon as possible. "Brick packing" divides the timeline into fixed periods, with the assumption that no pop-up tasks will be present, and puts hard deadline tasks to the specified timeline and uses priority and epoch times to pack tasks in the timeline, as shown in Figure 1.4. However, most of the tasks are fluid tasks, and there may also be pop-up tasks due to the nature of the sensor environment.

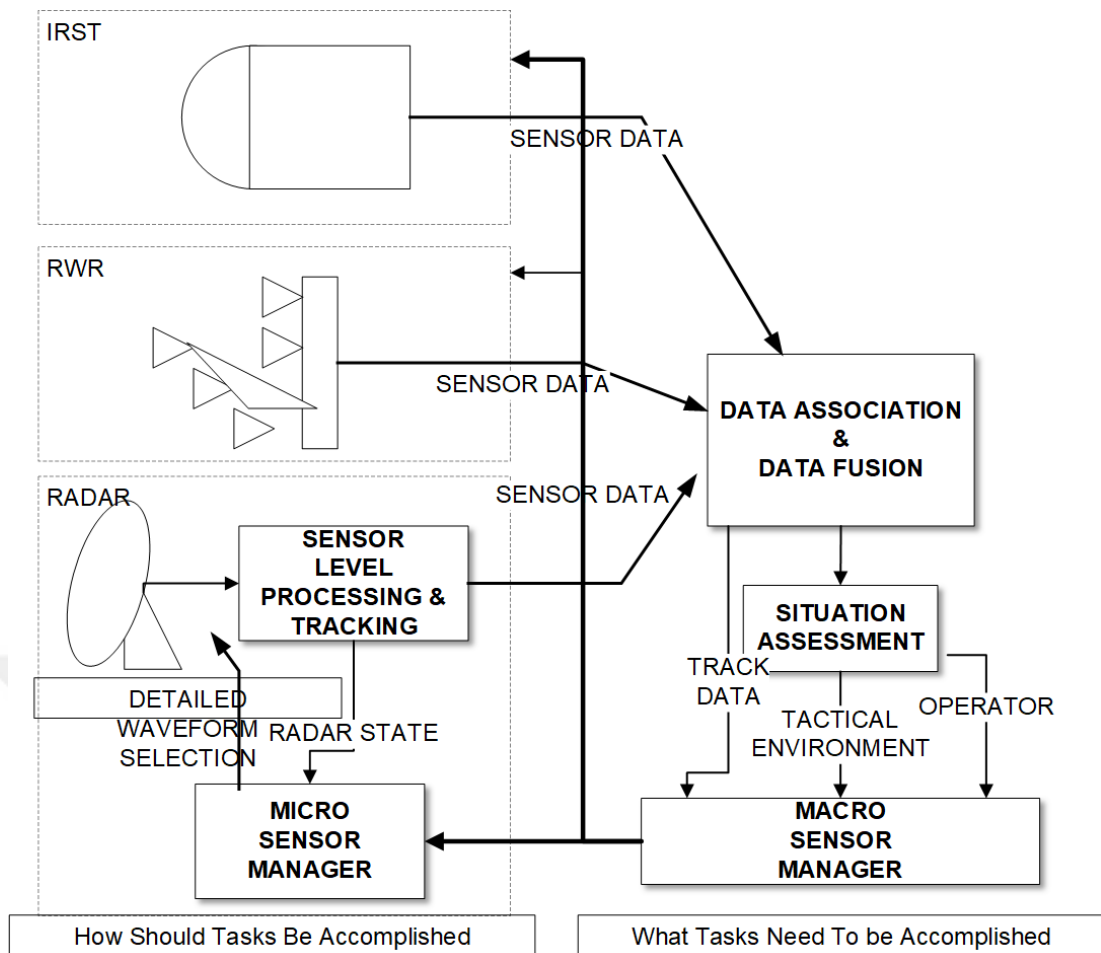


Figure 1.2 : Partitioning sensor management into macro and micro elements for multisensor systems.

The "best first" algorithm is best suited for macro-level task scheduling, and "brick packing" may be a good solution for micro-level SM architecture. Sensor scheduling approaches can also be categorized into myopic sensor scheduling approaches and non-myopic sensor scheduling approaches according to the scheduling time frame. Myopic sensor scheduling approaches only take into consideration the function of the next step; however, in non-myopic approaches, the function values of the following N steps are taken into consideration. Non-myopic sensor scheduling approaches are better than myopic approaches at the cost of increased computation [2].

An automated SM system shall make decisions to select sensor tasks in accordance with their importance. These decision-making techniques differ substantially at the micro and macro levels. At the micro level, algebraic figures of merit are used to make decisions about performance, suitability of mode, and loading. In contrast, at the

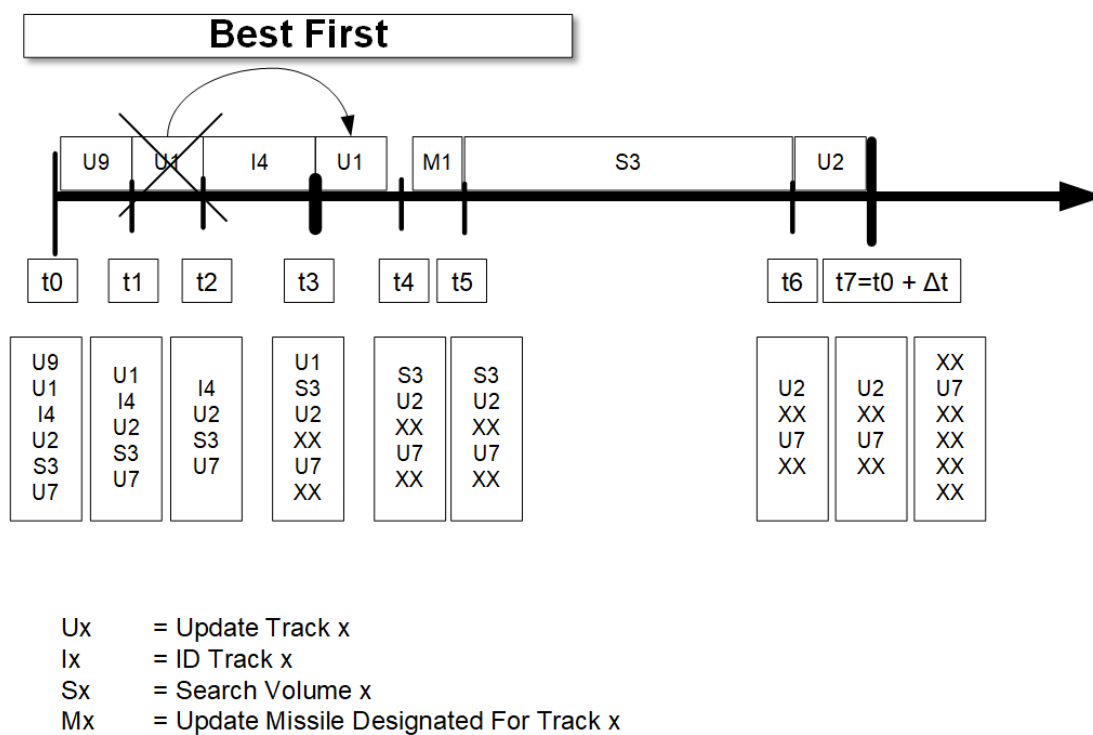


Figure 1.3 : Best first scheduling approach.

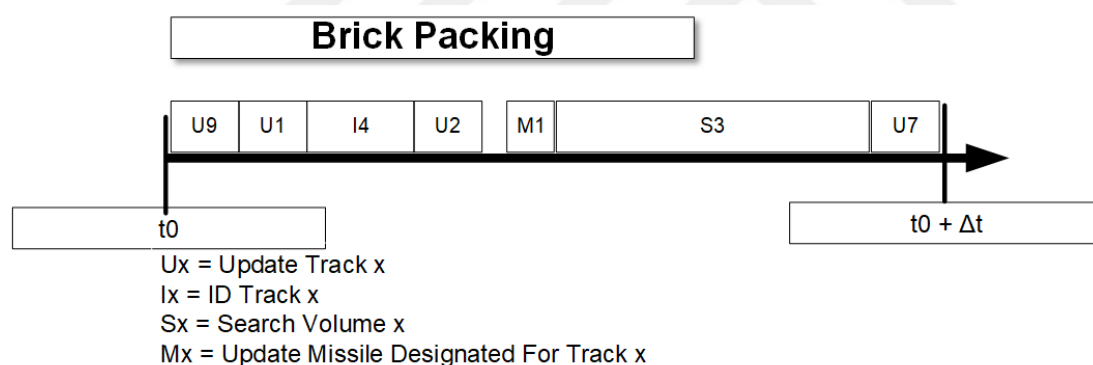


Figure 1.4 : Brick packing scheduling approach.

macro level, high-level reasoning takes place, which results in decisions that system operators normally make. Expert systems approaches are suited for this control.

Figure 1.5 shows a sample SM application. The proposed architecture is a feed-forward design in which management decisions predicted to achieve the desired result are fed forward from the macro-manager to the micro-manager to control the sensor.

As a conclusion in SM, two particular steps shall be taken. Firstly, a sensor management model shall be established, which consists of an objective function obeying some rules. Secondly, the optimal scheme from the objective function shall be obtained by traversing through all potential solutions or using optimization algorithms [6]. Approaches for modeling the objective function can be classified into four types, namely, the task-based approach [7], the information-driven approach [8], risk-based approach [9] and threat-based approach [10]. Although some important technical indicators can be obtained through the first two approaches, such as target detection probability and target tracking precision, actual operational requirements are not considered. Risk-based and threat-based approaches consider the operational context where the sensors are working. Hence, they seem to be most applicable to real-life scenarios. Risk-based approaches can also be subdivided into heuristics/rules-based [9] or Bayes-optimal approaches [11].

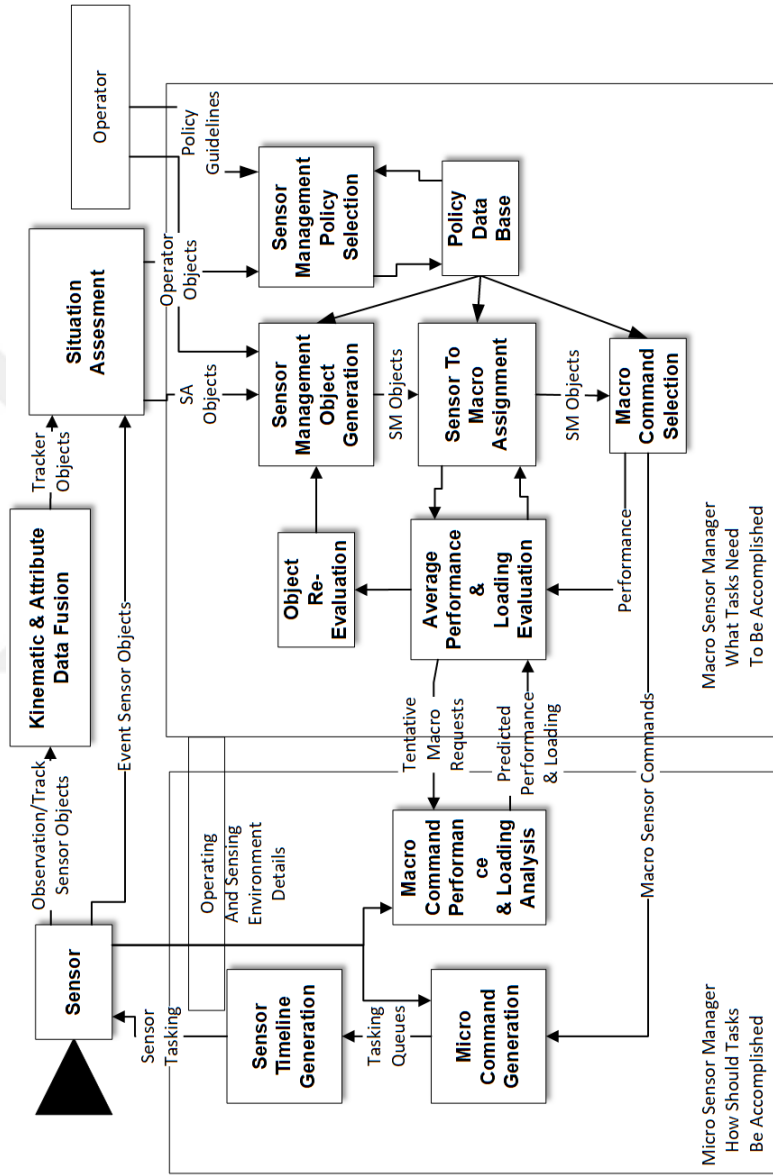


Figure 1.5 : Sample SM application.

The mentioned SM techniques are all applicable to the RRM of MPARs. Since MPAR executes multiple functions simultaneously, the limited time, energy, and computation resources shall be managed, and these resources shall be allocated to different tasks resulting from the requested functions to be performed. Thus, RRM in MPAR shall perform task prioritization and scheduling of these tasks while selecting the best parameters of the radar to fulfill the task requirement. The MPAR radar resource management high-level block diagram is shown in Figure 1.6.

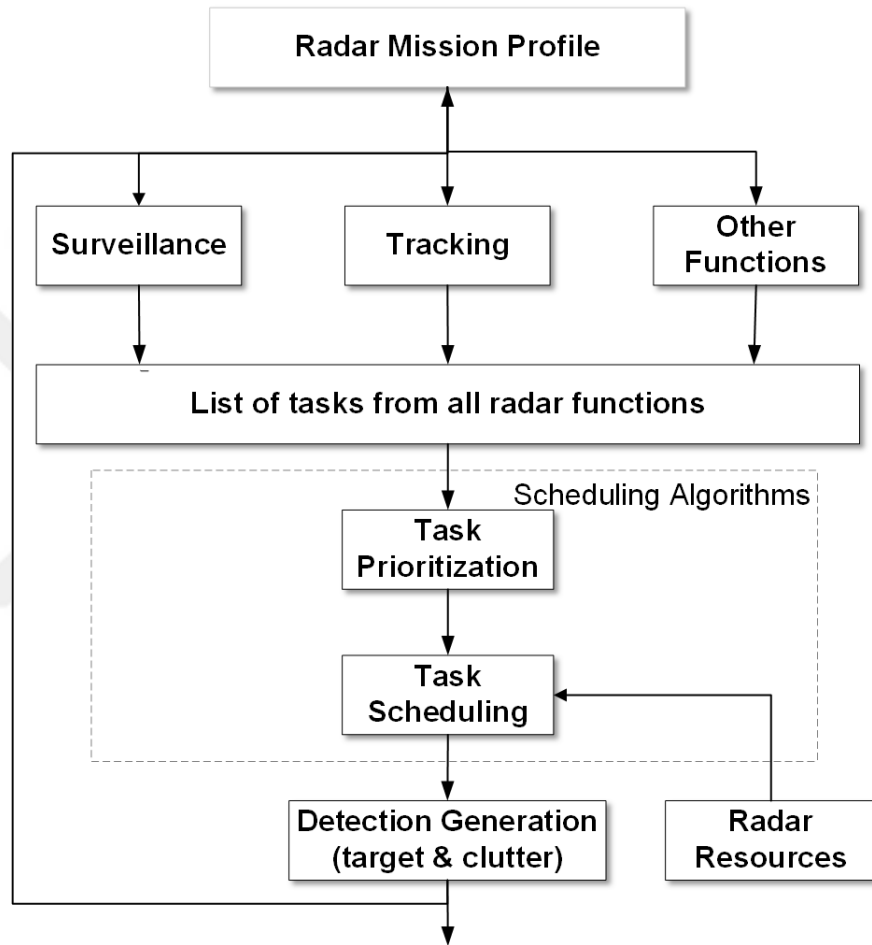


Figure 1.6 : MPAR RRM model.

MPAR performs multiple functions, including surveillance and tracking. Each function may consist of one or more tasks. These tasks shall be prioritized before they are scheduled for execution. The task prioritization process emphasizes the weight of the urgent tasks, which may lead to performance degradation or even the dropping of lower-priority tasks. Resource management problems try to solve task prioritization or task scheduling problems individually or simultaneously.

A detailed survey of radar resource management algorithms is given in the authors' paper [12] as well as book chapter [13]. Although the initial paper categorized the algorithms into six categories, including benchmark algorithms (actually, they are benchmark problems), finally, the book chapter categorizes the RRM algorithms into 5 categories after reviewing more than forty-three papers. The first three categories are adaptive scheduling algorithms, but the last two are resource-aided. Some papers do not exactly fall into adaptive or resource-aided algorithms; they are included in the category that the author thinks is more relevant. These categories are summarized below.

The Artificial Intelligence (AI) algorithms category includes neural network approaches [14], expert system approaches [15], and fuzzy logic [16] approaches. An entropy approach [17] is also included in this category. Dynamic Programming (DP) Algorithms [18] attempt to solve task prioritization and scheduling problems simultaneously. DP tries to decrease the computation needed to brute force, solving the problem of total performance gained by different alternative selections. DP approach is a nonlinear optimization method, and it is a promising solution to RRM problems. However, the mathematical formulation and the numerical optimization are more complex than the other algorithms. Q-RAM algorithms [19] are based on the concept of Quality of Service (QoS). The radar is optimized to keep an acceptable level of QoS, which is a cost function of performance. Q-RAM algorithms are nonlinear optimization methods. Waveform-aided algorithms [20] improve the radar resource requirements by reducing time, energy, and processing budget via waveform selection. In MPAR, different waveforms can be used for each function. Waveforms can be selected using neural network approaches or other possible optimization techniques. Adaptive update rate algorithms [21] use a non-uniform update rate of the target according to clutter characteristics, target maneuvering level, and the required tracking performance. These algorithms optimize the Kalman filter update intervals with large intervals, yielding less resource consumption. Due to this property, they are categorized in the resource-aided algorithms. Optimal adaptive rate is stated to be an ongoing research topic. However, the problem with adaptive update rate algorithms is that the noise model of the target changes with the adaptive update rate, which should be modeled carefully.

The national thesis database was also searched for radar resource management studies. The most comprehensive study [22] investigates RRM techniques for MPAR; different RRM techniques are tested, such as adaptive update rate, dynamic task prioritization, tracking, and task interleaving. Two schedulers are examined for real-time RRM for MPAR. Another study compares Q-RAM-based methods with methods of feasible directions using Monte Carlo simulations. Both methods are investigated in terms of optimality and convergence speed [23, 24]. In another thesis on RRM [25], the adaptive update rate algorithm applied for the Alpha-Beta filter is extended to the Kalman filter. An application of fuzzy logic for RRM has been explored in [26]. In [27], an independent subtask approach is used to convert the optimization problem to a known integer linear programming problem. The optimization objective is to increase the overall tracking quality in real-time under resource constraints.

From the time netted radars have been shown to offer increased detection performance [28], networked radar research has attracted the attention of researchers who introduced the concept of network-based radar resource management. The sensor netting concept is not new and has been applied to military naval systems for decades [29]. The approach to the networked radar resource management problem has been divided mainly into two categories. In the first category, the target tracking accuracy is tried to be improved with limited illumination resource constraints. In the second category, the illumination resource consumption for a specified target tracking performance requirement is minimized.

A type of networked RRM named coordinated radar resource management is discussed in the book Chapter 5 [12] and also in the paper [30] also published by the book authors. The authors call the RRM problem coordinated radar resource management in which radars share their tracking data and plots to enhance the performance compared to individual radar operations. The conclusion is that coordinated resource management provides the same level of track completeness with the added value of decreasing track occupancy and frame time.

Networked RRM aims to optimize the radar resources at the task, risk, mission, or threat levels. The overall optimization goal is generally represented by the Cramér–Rao Lower Bound metric, which is mathematically modeled with variables such as power, bandwidth, dwell time, etc. After this, an optimization is applied with

the optimization goal, and the parameters obtained from the result are fed back to the radars to be applied for the next epoch of the optimization cycle. If the optimization is done for the next cycle, this approach is named myopic and if it is done for the next N cycles, this optimization is named as non-myopic.

Different optimization parameters are used in the literature. The first approach aims to maximize the tracking accuracy with limited illumination. Single target tracking problem with networked radars is investigated in [31] using a two-step optimization strategy: first, defining the revisit time and second, assigning which radar to take the measurement from the target. Power allocation of networked radar is also studied for unmodulated continuous wave radar network [32]. For a given total power budget at each time index, the proposed optimization algorithm aims to allocate the power resource that minimizes the predicted Bayesian Cramér–Rao Lower Bound (BCRLB) subject to the power limits of individual radar. Power and bandwidth are optimized jointly to achieve the best available tracking accuracy [33]. The objective function of predictive BCRLB is minimized with the specified power and bandwidth constraints. The objective function is formulated as a convex function and optimized using gradient projection. The problem of joint beam selection and power allocation in netted colocated Multiple Input Multiple Output (MIMO) radars is handled in [34]. A cooperative target assignment and dwell allocation (CTADA) optimization framework is developed in a phased array radar network in [35]. The optimization problem is a mixed-integer nonlinear and nonconvex optimization problem with two correlated adaptable parameters. The problem is solved using a two-step optimization approach. In the first step by introducing an auxiliary vector, the original nonconvex problem is relaxed as a convex one, and then solved using the convex optimization toolbox. According to the results of the relaxed problem, an efficient heuristic dividing algorithm is used to find a suboptimal solution to the original non-convex problem. In [36], a joint node selection and power allocation (JSPA) strategy is developed with the objective of tracking multiple targets. The proposed method implements the optimal resource allocation based on the feedback information in the tracking recursion cycle to improve the worst-case tracking accuracy with multiple targets within a decentralized network architecture to reduce communication requirements. Most of the optimization problems take into account that target tracking performance requirements are same for

multi target tracking, however in [37], a resource aware design is introduced taking into account of different tracking accuracy requirements for each target. According to an adaptive cost function that considers different tracking requirements, a scheme of node selection and power allocation for multiple target tracking has been proposed. Clutter is also another parameter that affects radar performance parameters. So there are also studies that aim to optimize the radar network in a clutter environment. The power allocation problem of a networked radar tracking a single target in clutter is formulized as a nonconvex optimization problem using BCRLB as optimization criterion in [38]. Another study considered Joint Power and Bandwidth Allocation (JPBA) strategy in a asynchronous radar network to track targets in clutter [39]. An asynchronous resource allocation model is built in which a periodic allocation strategy is suggested. BCRLB is derived by incorporating the information reduction factor as a performance metric for the JPBA strategy. Finally, the asynchronous power and bandwidth allocation optimisation problem are formulated by minimising the tracking rootmean- square error with given power and bandwidth budgets, which is non-convex but monotonic. Finally, by introducing the branch-reduce-and-bound algorithm, a global solution to the optimization problem is obtained. Another variant of the algorithm takes into account detection threshold and power optimization in a target tracking application in clutter [40]. The nonlinear and nonconvex optimization problem is solved using a two-stage optimization method. Radar-to-target assignment, revisit time, and dwell time are jointly optimized in [41] using an improved particle swarm optimization algorithm. Another research area for networked radar resource management is the minimization of illumination resource consumption for specified target tracking requirements, which enhances the Low Probability of Detection (LPI) of networked radars. An allocation model of radiation power and dwell time based on LPI performance for radar network systems is established in [42]. Another research on LPI radar network has investigated sensor selection and power allocation problem that aims to minimize the total transmitted power of a radar network on the basis of a predetermined Mutual Information (MI) threshold between the target impulse response and the reflected signal [43]. Resulting optimization problem is non-convex and it can be solved by seperating power allocation problem from sensor selection problem. Shi et al [44], has introduced a novel joint optimization method which considers revisit

interval, dwell time and transmitting power of the networked radars. There are other LPI-based variants that simultaneously optimize node and power [45], revisit and dwell time [46], radar-to-target assignment, revisit time, dwell time and power allocation [47], radar-to-target assignment, revisit time, dwell time and bandwidth allocation [48]. Dai et al [49], utilized the detection capability of the sensors on the threat in order to decrease the detection probability of the networked radar sensors. Recent research on the subject has been performed by Shi et al. by combining the radar node selection and collaborative transmit resource allocation problem by collaboratively optimizing radar node selection, illumination power and signal bandwidth allocation for the desired multi-target tracking performance and some system resource constraints [50]. The latest research papers on the subject by Shi et al. have been on power optimization for a combined radar and communication system [51, 52]. Quality of service-based network radar resource management is also an active research area. In QoS based optimization the objective of the radar network resource management problem is to select operational parameters and therefore also allocate radar node resource, such that utility generated by all tasks is maximised subject to the resource constraint. Different quality of service requirements can be specified for different mission phases [53]. Yan et al. proposed a Quality of Service based Resource Allocation (QoS-RA) scheme which divides radar sensors into several groups to illuminate multiple targets separately but also optimize the transmit resource of the radar sensors in different groups as well.

1.3 Contribution of the Thesis

The thesis has the following contributions to the broad subject of networked radar resource management.

A networked radar resource management algorithm that aims to exploit the effect of utilization of target priority as well as target maneuver to adaptively track targets in a networked ADS whose Fire Control Radars (FCRs) are cooperating compared to previous studies that utilize only target priority or target maneuver for radar resource management.

The original contribution of this subject is given published in the following research article.

- **Tuncer, O.**, Cirpan, H.A. 2023. A Networked Radar Resource Management Approach Utilizing Target Priority and Maneuver for Cooperative Air Defense Fire Control Radars. *IEEE Access*, vol. 11, pp. 136279-136291, 2023, doi: 10.1109/ACCESS.2023.3337799.

A surrogate-based optimization strategy is developed to select the minimum number of radars and selection intervals that satisfy the required tracking quality for each target. Tracking quality requirements used in the algorithm are adaptively selected using the priority of the targets. Apart from the previous work, the proposed method combines target priority-based adaptive tracking and optimization methods to select the tracking radars in a networked ADS.

The original contribution of this subject is published in the following research article.

- **Tuncer, O.**, Cirpan, H.A. 2022. Target Priority Based Optimisation of Radar Resources for Networked Air Defence Systems. *IET Radar Sonar Navig.*,16(7), 1212– 1224

In addition to the contributions to networked radar resource management, we have developed a novel adaptive threat evaluation system that can be used to prioritize targets on networked radar resource management algorithms based on threat priority. An adaptive fuzzy rule-based threat evaluation system based on genetic fuzzy systems is proposed that allows full automation of fuzzy logic rule generation through a survey applied to air defense experts and near real-time tuning of the fuzzy rule base during ADS operation. Apart from the previous work, this study utilizes genetic fuzzy systems to automate fuzzy rule base system components during training and in the context-dependent operational mode.

The original contribution of this subject is published in the following research article.

- **Tuncer, O.**, Cirpan, H.A. 2023. Adaptive fuzzy based threat evaluation method for air and missile defense systems. *Information Sciences*, 643, 119191.

1.4 Thesis Outline

The rest of the thesis is organized as follows. Chapter 2 gives a brief explanation of networked ADS radars. The building blocks of the networked ADS are introduced,

and a brief explanation of the functions performed within these blocks is given. Chapter 3 presents a novel adaptive threat evaluation system for ADS trained to learn the TE system model from a survey applied to air defense experts, allowing real-time context-dependent adaptation according to the changing threat environment. Resource management techniques of networked air defense radars using adaptive tracking techniques are presented in Chapter 4. An algorithm that utilizes adaptive target tracking based on the target priority and maneuver of the targets is presented along with the simulation results in various threat scenarios. Chapter 5 presents target priority-based optimization algorithms used to select the minimum number of radars and selection intervals that satisfy the required tracking quality for each target. Chapter 6 concludes the thesis by highlighting the primary outcomes with a summary of the thesis's contributions and giving suggestions for future work.

2. NETWORKED AIR DEFENSE SYSTEM RADARS

Legacy ADSs shown in Figure 2.1 rely on hierarchical connectivity between the system elements such as Fire Control Center (FCC), Fire Control Radar (FCR), and Missile Launching Systems (MLS) under a centralized command and control authority. An increased number of modern threats of mixed types have led to the degradation of air defense performance under this command and control structure. Centralized command and control structure does not allow sharing of radar and weapon resources among different ADSs. Adapting legacy systems to the current rapidly changing threat environment within a short amount of time requires a lot of investment and labor.



Figure 2.1 : Legacy air defence system architecture.

The networked ADS concept, which is shown in Figure 2.2 is based on an open system architecture that enables direct communication of ADSs by sharing their sensor and weapon resources to increase overall air defense effectiveness. In networked ADS, systems are connected by reliable, high bandwidth, and secure communication means. This connectivity enables various system services to be shared among the network

participants, eliminating the bottleneck posed by the hierarchical legacy command control structure.

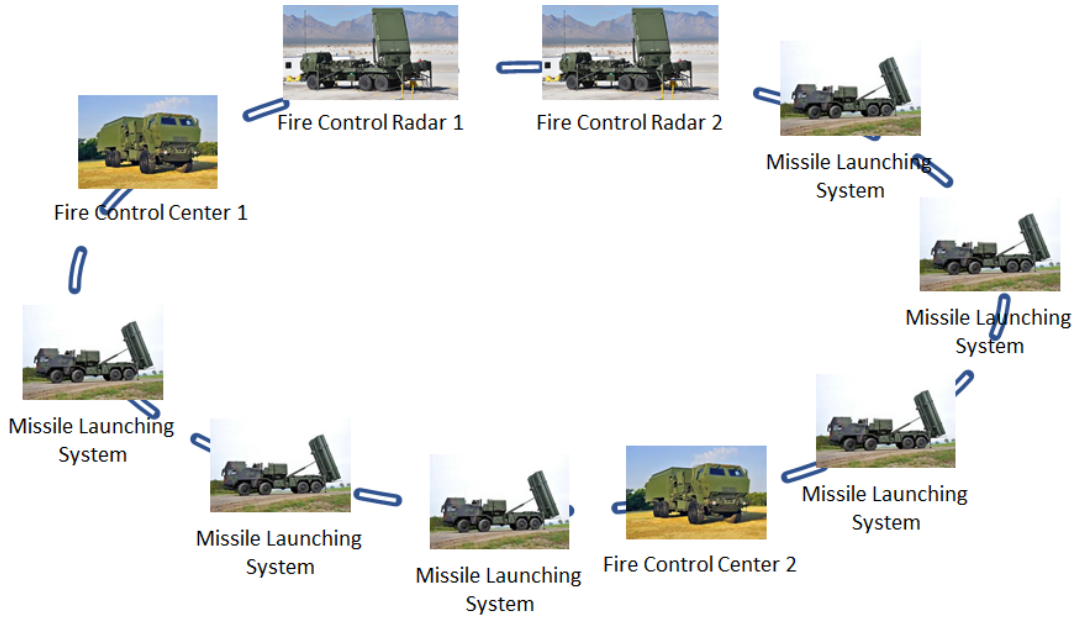


Figure 2.2 : Networked air defence system architecture.

Modern ADS utilize MPAR for their FCRs, which perform multiple functionalities such as searching and tracking at the same time. However, these MPARs have limited resources, which may be overwhelmed by the increased threat environment. Networked ADS brings up the concept of networked ADS radars, which aims to manage limited radar resources at the system of system level to increase ADS effectiveness.

A simplified block diagram for a configuration of networked ADS is shown in Figure 2.3. Targets are detected by the search capability of the multifunction FCRs of ADS. Detections $\mathbf{Y}_k$ from the targets are collected in a fusion center to generate tracks $\mathbf{T}_k$ forming the common combined air picture. Next, targets are collectively prioritized according to the air defense mission carried out by the networked ADSs. The evaluation of targets is followed by an engagement decision process where available weapons are assigned to targets that are eligible for engagement. In order to increase the overall system performance, the key functionality is to control the working parameters of FCRs according to a predefined rule set or an optimization objective. Target priority and other features of the target, such as maneuver, can be

used to control the parameters of the FCR to share radar resources, which balance the tracking and surveillance load and increase overall air defense effectiveness. Targets positively assessed for successful interception are dropped from the tracking list. This information is also feeding the FCR control block, which releases radar resources assigned to these targets.

The air defense starts with the detection of the targets, so increasing sensor performance via networking is the key process. Networked radar has attracted the attention of researchers after they are found to provide increased detection performance [28]. The benefits of coordination in the RRM for networked MPAR have been shown over radars utilizing independent RRM [30]. As modern ADSs utilize MPAR for their FCRs, they can also benefit from the advantages provided by coordinated RRM. The term cooperative FCR is used in the thesis for the air defense MPAR FCRs, which have the capability to share their radar resources to increase system effectiveness.

In networked ADSs which consist of multiple MPARs, radar resource management is performed at the system of system level in addition to individual radar resource management functionality of each MPAR. This RRM shall be adaptive to the changing threat environment in order to maximize the system's effectiveness. The next section will give brief explanation on how RRM is performed for cooperative air defense FCRs.

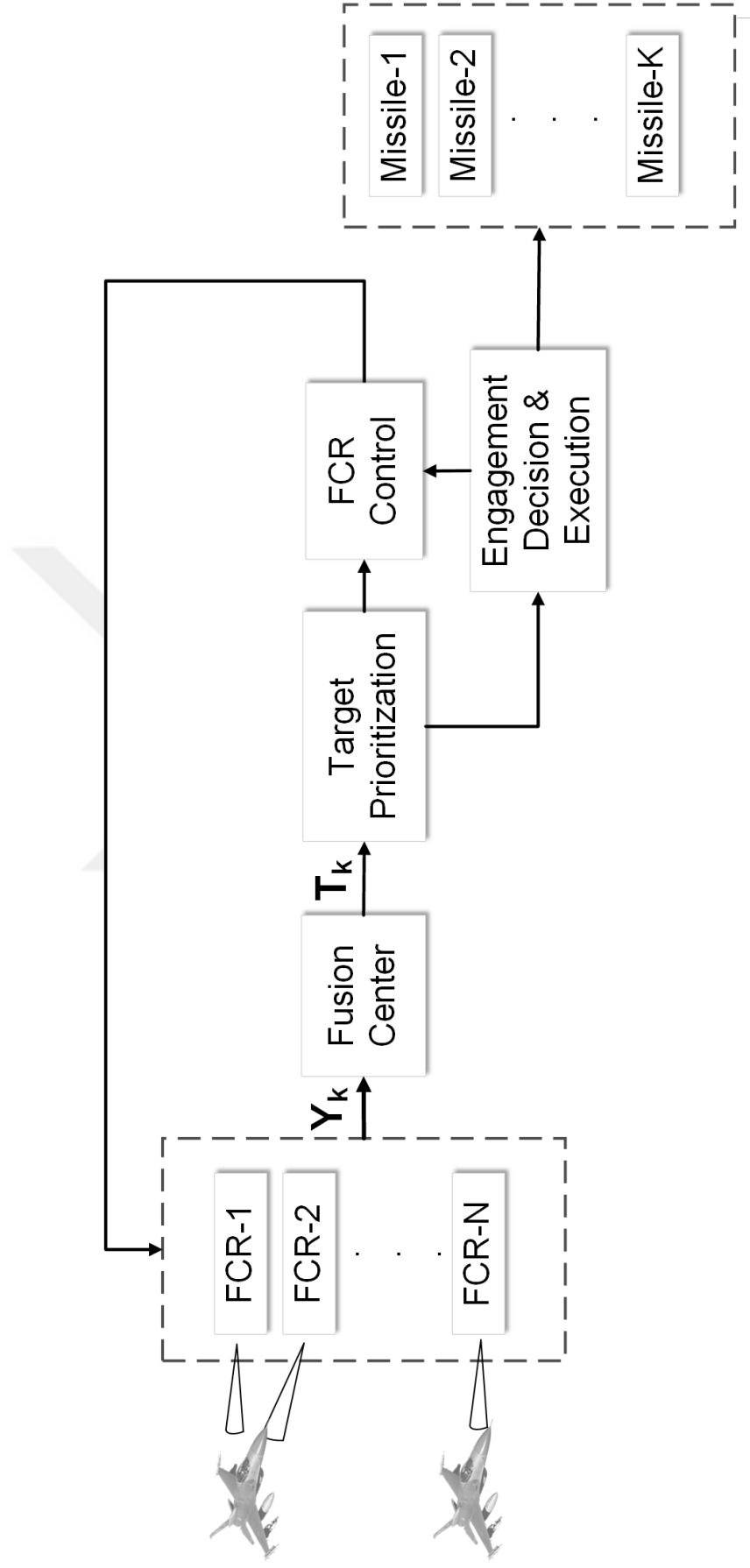


Figure 2.3 : Networked ADS block diagram.

2.1 Networked Air Defense System Components

As targets can have dynamic trajectories and time-variant priorities, limited FCR resources shall be adjusted dynamically. The adaptivity of RRM can be provided by changing the duration, waveform, or revisit time of tracking pulse of the FCR, which is called adaptive tracking [54]. Adaptive tracking requires filters such as Interacting Multiple Model (IMM) that detect target maneuvers that can be used to adjust the dwell time on the target. Target priority is also another essential feature that can be used in adaptive tracking applications [55,56].

The following subsections briefly explain each building block in the networked ADS system shown in Figure 2.3.

2.1.1 Fusion center

Detections from the individual FCR are gathered in the fusion center to form the combined air picture for the networked ADS. Global tracks are formed from individual detections after confirmation looks of the networked radars. Formation of the tracks starts with the data correlation process, which is comprised of gating and data association. Gating eliminates observation-to-track pairings by selecting the measurements $\mathbf{Y}_k$ that satisfy the gating conditions, and observations satisfying the gating relationship are considered for track update [5]. Subsequent detections from the networked FCR are associated with the formed tracks using data association methods such as the Global Nearest Neighbour (GNN), the all-neighbors data association approach (PDA, JPDA), and Multiple Hypothesis Tracking (MHT). GNN, referred to as single hypothesis or sequential most probable hypothesis tracking, is the simplest and most widely used method for data association. The measurements are partitioned according to their origin to form a hypothesis. GNN selects the best hypothesis about all of the measurements received in the past [57]. Unassociated detections $\bar{\mathbf{Y}}_k$ are passed to the initiator processor. The overall block diagram of the fusion center is shown in Figure 2.4.

Targets that threaten ADSs usually have high maneuver capability. These targets tend to maneuver when detected and tracked by the ADS to break the lock of tracking radar

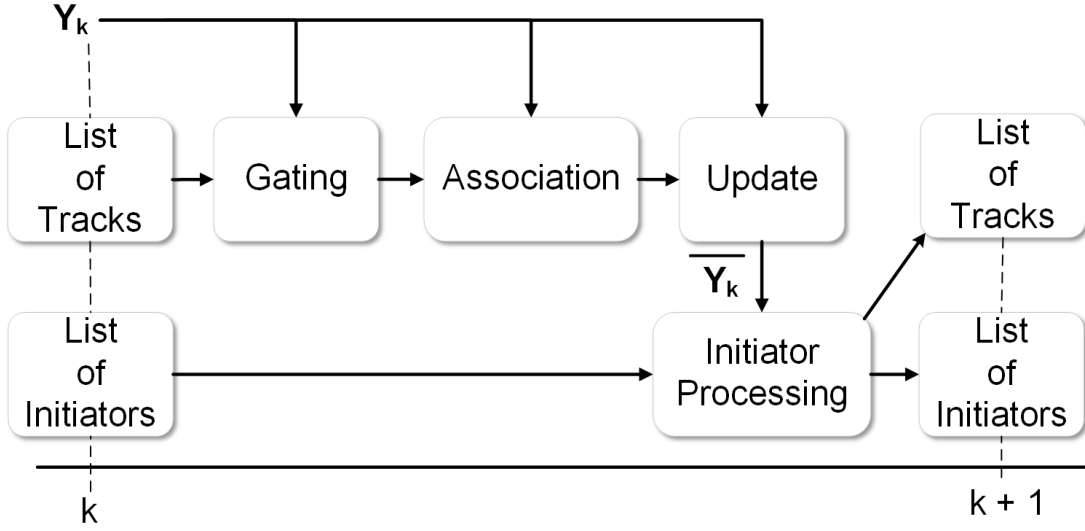


Figure 2.4 : Block diagram of a fusion center.

and a subsequent interception. To track those highly maneuverable targets, Interacting Multiple Model Extended Kalman Filter (IMM-EKF) has been widely used [58–60]. EKF and the IMM filter working principle will be briefly described without going into detail.

EKF algorithms' apparent simplicity, optimality, tractability, and robustness have made it one of the most widely used methods for tracking and estimation. A KF is applied to non-linear process and measurement models by linearizing the models in the EKF. EKF update equation is of the same form as the linear KF:

$$\hat{\mathbf{x}}(k|k) = \hat{\mathbf{x}}(k|k-1) + \mathbf{K}(k) \{ \mathbf{y}(k) - \mathbf{h}[\hat{\mathbf{x}}(k|k-1)] \} \quad (2.1)$$

where $\mathbf{h}[\hat{\mathbf{x}}(k-1|k)]$ is generally a nonlinear measurement function, $\mathbf{K}$ is the gain. The gain computation is similar to linear KF:

$$\mathbf{K}(k) = \mathbf{P}(k|k-1) \mathbf{H}_x^T(k) [\mathbf{H}_x(k) \mathbf{P}(k|k-1) \mathbf{H}_x^T(k) + \mathbf{R}(k)]^{-1} \quad (2.2)$$

$\mathbf{H}_x$ is the linearized measurement matrix defined by

$$\mathbf{H}_x(k) = \left. \frac{\partial h}{\partial x} \right|_{\mathbf{x}=\hat{\mathbf{x}}(k-1|k)} \quad (2.3)$$

and $\mathbf{P}$ is the state estimation covariance matrix, and $\mathbf{R}$ is the measurement noise covariance matrix. $\mathbf{H}_x$ has dimensions $d \times m$ where d is the dimension of the estimated state vector and m is the dimension of the measurement.

The IMM algorithm combines state hypotheses from multiple filter models to get a better state estimate of highly maneuverable targets. The motion of the target is described by multiple models in IMM. The probability of each motion model is found using the model's likelihood function. A transition probability is also used to switch between different models. The weighted sum of estimates from the subfilters is calculated using a posteriori probabilities as the weighting factors to obtain the combined estimate. IMM allows a smooth transition from different filter models and performs better than the switching schemes [61].

IMM algorithm shown in Figure 2.5 consists of four stages, namely interaction of the estimates, filtering, model probability update, and combination of the estimates. At each instant, an initial estimate of each filter belonging to a particular mode is computed by mixing the state estimates of all filters. This is followed by filtering composed of prediction and update steps for each mode. Finally, the weighted sum of the updated state estimates of all filters is combined to yield the state estimate. [61,62] explains each step of the IMM algorithm in detail. Several filter models can be used in the IMM algorithm. The Constant Velocity (CV) model produces the best position and velocity estimate for non-maneuvering targets with the assumption of a continuous-time white noise process for target accelerations. Other models include Constant Acceleration (CA) and Constant Turn (CT) rate models. The state transition matrix for the CT model is defined to perform a constant-speed turn maneuver along the trajectory defined by the state estimates of velocity and acceleration. Model probabilities can be used to indicate target switching from a CV motion through the CA or CT model or vice versa. This probability information can be used in adaptive tracking applications where targets with high dynamics are tracked more frequently by the FCR of ADS.

2.1.2 Threat evaluation

The degree of threat posed by targets depends on their capability and intent. Threats' ability to damage the Defended Assets (DAs) is referred to as the capability and desire to harm reflect the intent. These features of the targets can be utilized while evaluating the threat degree of targets and prioritizing them accordingly. While target priority is

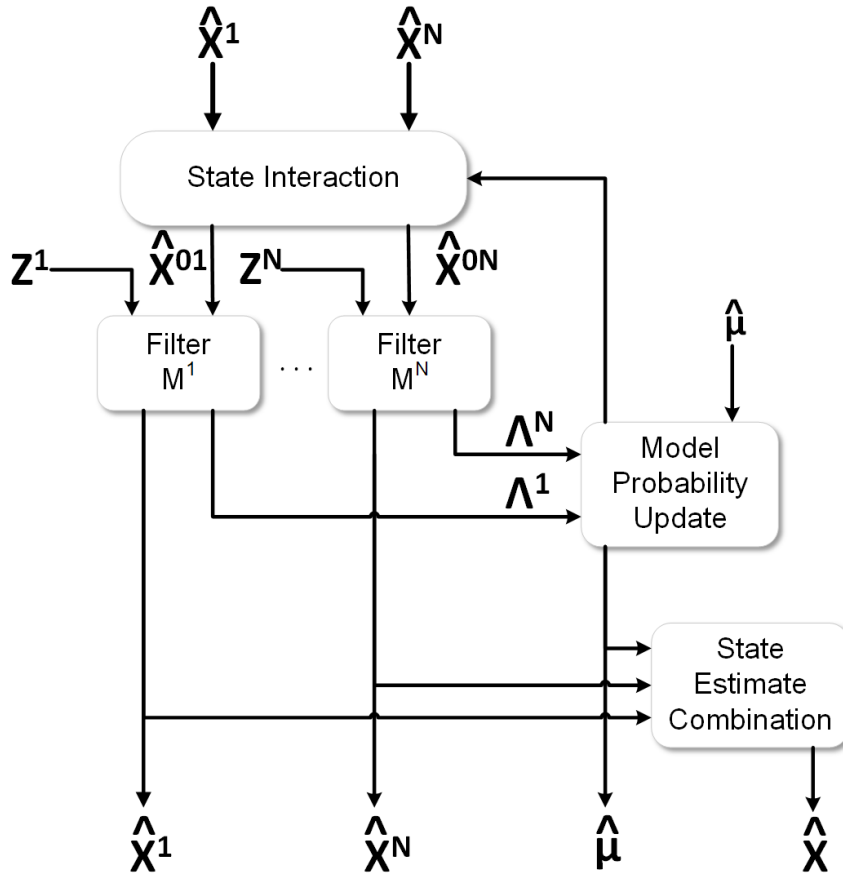


Figure 2.5 : Block diagram of IMM algorithm.

mainly used to manage weapon resources, benefits of using target priority to manage radar resources have been shown in the literature [30, 55, 56].

An important distinction of target prioritization in networked ADS from target prioritization in a single ADS is that in networked ADS; targets are globally prioritized by considering proximity features of targets to DAs according to the overall defense design under consideration. Hence, globally determined target priority can be used to adjust adaptive tracking rates of FCR in networked ADS.

2.1.3 Engagement decision and execution

Targets with high priority are engaged by the networked ADS. Engagement decision is made through the availability of an engagement timeline consisting of the first shot and last shot time. Engagement decision is made manually by the operators or automatically through either semi-automatic or automatic working modes of the system. In semi-automatic mode, the fire control solution is executed automatically

by the operator input, and in automatic mode, decision and execution are done automatically by the network without the need for operator input. The execution phase consists of selecting the launcher and the missiles, firing and guidance of the missiles, and kill assessment phase of the engagement, where the target's destruction is reported.

2.1.4 Networked radar resource manager

FCR control block adjusts the working parameters of the fire control radars to increase overall system effectiveness according to a specified algorithm that is subject to change according to the air defense mission. The control parameters include waveform selection, dwell time selection, radar selection, tracking rate adaptation, and power selection of the networked radars [63]. Inputs from the Engagement Decision and Execution block can also affect the radar control. For example, the accurate determination of successful target engagement allows target tracking to be terminated, releasing radar resources for upcoming target tracking tasks. Different types of resource management architectures can be designed, such as centralized or distributed management for radar networks.

In centralized management, a single resource manager schedules all radars in the network. The resource manager may be inside one of the radar nodes or may be deployed elsewhere apart from the radar nodes. The main advantage of centralized management is the resource manager can utilize all available radar resources. The advantage of centralized management is the ability of the However, the centralized resource management is vulnerable to the communication performance including channel availability and latency. The block diagram of the centralized management is shown in Figure 2.6.

However, in distributed management, each radar manages its resources independently and has its individual resource manager. Resource managers communicate with each other through the communication channel. This distribution eliminates the reliance on the communication channel for resource management since each radar can manage their resources even if the communication between the nodes diminishes. However, it is difficult to fully utilize all available radar resources due to the nature of distributed

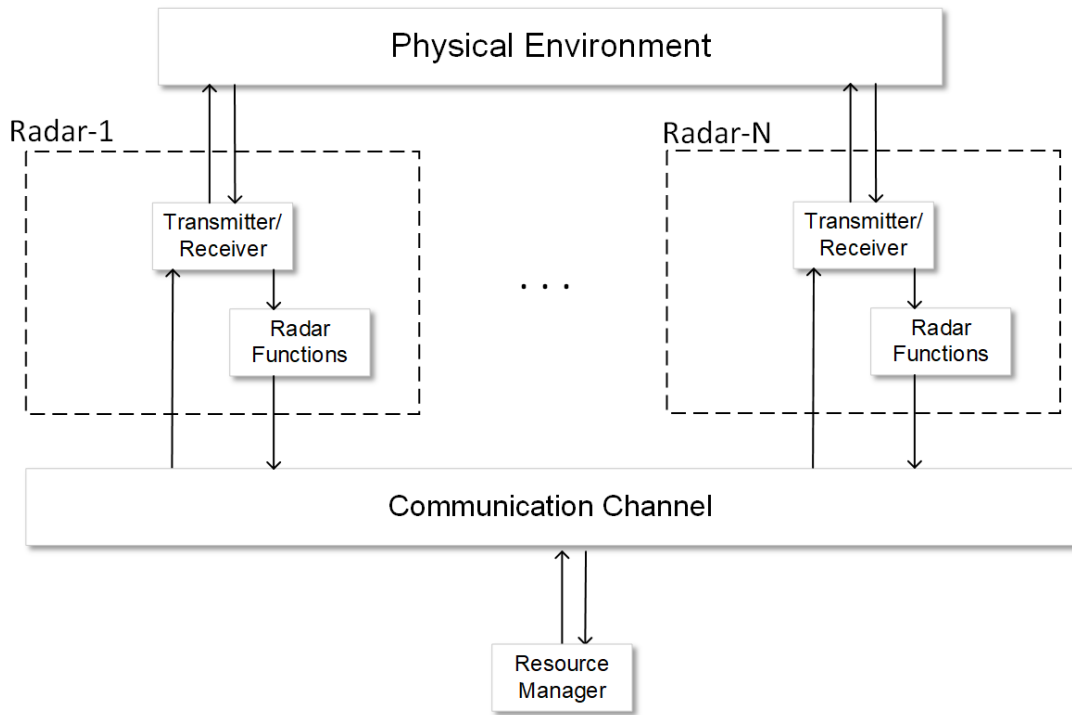


Figure 2.6 : Centralized RRM block diagram.

scheduling optimization. The block diagram of the distributed management is shown in Figure 2.7.

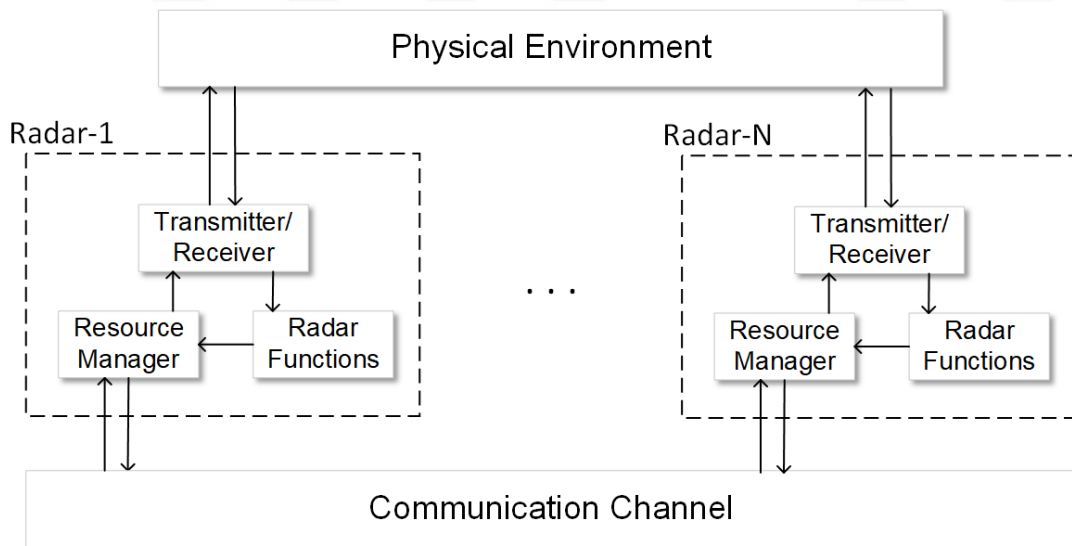


Figure 2.7 : Distributed RRM block diagram.

3. A NOVEL ADAPTIVE THREAT EVALUATION SYSTEM FOR ADS

ADS detects, tracks, classifies targets and evaluates the degree of threat posed by each target before assigning a weapon to engage them. Threat evaluation (TE) is an essential function of ADS to decide and act against targets and significantly impacts the system's overall effectiveness. In ADS, TE not only helps to prioritize the threats for engagement in the weapon assignment process but also helps to adaptively reserve limited sensor resources for the most dangerous threats [56]. Thus, the TE function plays a crucial role in ADS effectiveness. Although threat evaluation is one of the most critical processes of an ADS, it is poorly defined because of the difficulty of reflecting operator understanding in real-time.

After ADS establishes the situational picture, targets are evaluated according to their capability and intent. Threats' ability to damage the DAs is referred to as the capability and desire to harm reflects the intent. Although the capability of a threat is easier to specify, deciding on the intent is a difficult and subjective process. Specific threat features such as heading, velocity, and maneuverability can be used to assess the intent [64]. The target's capability and intent features shall be utilized to determine the threat level, which is the output of the TE function. However, there is an inherent uncertainty of a target's threat level by looking at those target parameters, and it is subjective among air defense operators.

Different artificial intelligence (AI) methods have been applied to TE in ADS to reflect operator decisions. Two fundamental approaches are the Bayesian network approach [65] and the fuzzy set theory [66]. Bayesian networks are proven to handle uncertain events. In contrast, TE using fuzzy sets has the advantage that they can be built more quickly and have smoother output without fine discretization [67]. Conditional Probability Tables (CPT) shall be filled when using Bayesian Networks, and building a CPT is a challenging task with the increased number of parameters and related states. While both approaches apply to TE Decision Support System (DSS) application with their pros and cons, the ease of adaptation of fuzzy-based systems by adding

or changing the rules and ability to reflect expert knowledge has led them to be an effective solution for TE in air defense applications [68,69]. The fuzziness involved in threat degree assessment can be well modeled mathematically using fuzzy sets theory, leading to the usage of Fuzzy Rule-Based Systems (FRBS) in the ADS TE function.

FRBS is widely used in threat prioritization with their ease of adaptation in air defense applications [68–70]. FRBS maps between a crisp set of input data set to a crisp set of output using a set of processes named fuzzification, inference, and defuzzification as shown in Figure 3.1. In the last step, defuzzification, an inference is made based on a set of rules, and membership functions are used to map the fuzzy output into crisp output. Targets are prioritized according to their features and their proximity to DAs.

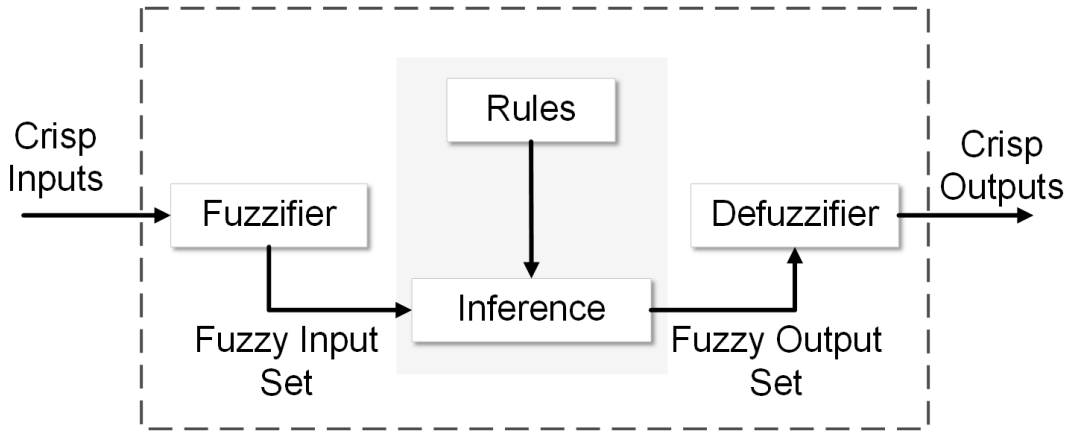


Figure 3.1 : Fuzzy rule-based system processes.

These features comprise the fuzzy variables of the FRBS, and the fuzzy rules are then formed to convert the fuzzified input set to the fuzzy output set. Hostility, target range to closest ADS, range to closest DA, target maneuverability, and target speed can be used as fuzzy variables for target priority determination. However, the manual definition of these FRBS rules and MFs is a demanding process that can be automated by Genetic Fuzzy Systems (GFSs).

In this chapter, a novel adaptive fuzzy rule-based TE system based on GFS is proposed, which learns the TE system model from a survey applied to air defense experts, allowing real-time operator input to tune the TE DSS during ADS operation, which is shown in Figure 3.2. The proposed method consists of an initial training mode where FRBS is trained using the output from surveys applied to subject matter experts. In the subsequent context-dependent adaptation process, FRBS is adapted by the

operators with real-time operational input, where TE DSS does not seem to comply with user experience in different operational contexts. Overall, the solution allows full automation of fuzzy logic rule generation through a survey applied to air defense experts and near real-time tuning of the FRBS during ADS operation. Apart from the previous work, this study utilizes GFS to automate FRBS components during training and in the context-dependent operational mode. Numerical performance results are also given for the application of the proposed method.

3.1 The Need for Automation of Threat Evaluation in ADS

As the threat evolves, an increase in saturation attacks mixed with various threat types pushes the limits of human cognitive load, and operator performance degrades with an improved threat environment [71]. ADS functions, including TE, shall be automated as much as possible to reduce operator workload. Well-defined cognitive models have been developed via surveys for replicating expert knowledge to air defense systems for threat evaluation [72]. Integration of these cognitive models and automation of TE function reduces the operator load while decreasing operator-related decision errors in stressful air defense operational environment [64].

Different possibilities exist for TE system automation using only or a combination of rule-based techniques, Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), bayesian networks, TOPSIS, neural networks, and fuzzy logic [73]. However, as the adversary's tactics change over time with the evolution of threat elements, the automated TE system shall be as adaptive as possible to changing battlefield requirements. An automated TE DSS shall be provided to air defense operators, which not only initially reflects the user's previous experience but also can adapt via user interaction with the changing threat environment. Among the many DSSs, FRBS has been shown to be effective for air defense applications due to its ease of implementation and adaptability [68,69].

Manually generating and tuning an FRBS is time-consuming, especially when the number of fuzzy variables, the membership functions (MFs), and the number of rules representing the underlying system is enormous. Also, when the knowledge base (KB) underlying the system changes, the FRBS has to be tuned again with current information. When FRBS is applied to TE as a DSS, quick changes in the battlefield

environment require automation in creating and maintaining the underlying FRBS through structural design and optimization methods.

There is a lot of published work carried out on finding efficient methods of FRBS structural design and optimization [74, 75]. Optimization of MF parameters of linguistic terms [76], weights of fuzzy rules [77], selection of defuzzification methods [78], rule base interpolation and reduction [79] and rule base correction [80] has been studied. Other studies in the subject area include supervised fuzzy clustering [81], combining rule antecedents [82] and multi-objective optimization [83]. In addition to the use of classical optimization methods in the design and optimization of FRBS [84], bioinspired techniques of evolutionary optimization have also been used [85]. Artificial bee colony, ant colony [86], particle swarm methods [87], and grey wolf algorithms [88] are among the bioinspired optimization techniques that are used.

It has been shown that a feedforward neural network could approximate any FRBS and vice versa [89]; hence, neuro-adaptive learning techniques can also be used to define and optimize FRBS, which integrates the benefits of both artificial neural networks and fuzzy logic [90]. Integration of fuzzy logic systems and neural networks allows them to complement each other by covering their drawbacks.

Using iterative neural network tuning techniques to adjust fuzzy sets and rules with input and expected output data is referred to as Neuro-Fuzzy. Since Neuro-Fuzzy systems combine fuzzy systems' capability to reflect expert knowledge and the learning capability of neural networks, there is a growing interest in Neuro-Fuzzy systems [91]. Pattern classification, solutions to regression problems, time series prediction, fault detection, industry problems related to civil engineering, robotics, agriculture, and creating solutions in the field of health area are examples of applications of Neuro-Fuzzy models [92,93]. Automation of FRBS-based TE function has also been shown using Neuro-Fuzzy systems applied to a dynamic system that adapts to changing battlefield conditions in time [94].

Genetic Fuzzy System (GFS) is another candidate hybrid approach that can be used to automate the definition and modification of the FRBS components used in TE [95]. GFS combines fuzzy logic and Genetic Algorithm (GA) to automate FRBS generation. GA allows large search spaces to be explored to find suitable solutions for FRBS

parameters. GFS also provides means to train and tune FRBS components and can be used for TE DSS automation. Utilization of GFS in the form of Genetic Fuzzy Trees (GFT) has been successfully applied to intelligent control of Unmanned Combat Aerial Vehicles (UCAV), which enable intelligent mission planning, routing, and direct control of weapons [96]. This success leads researchers to think about using GFS in warship air defense TE where GFS in the form of GFT can be utilized in the near future with the advance in computing technology [97].



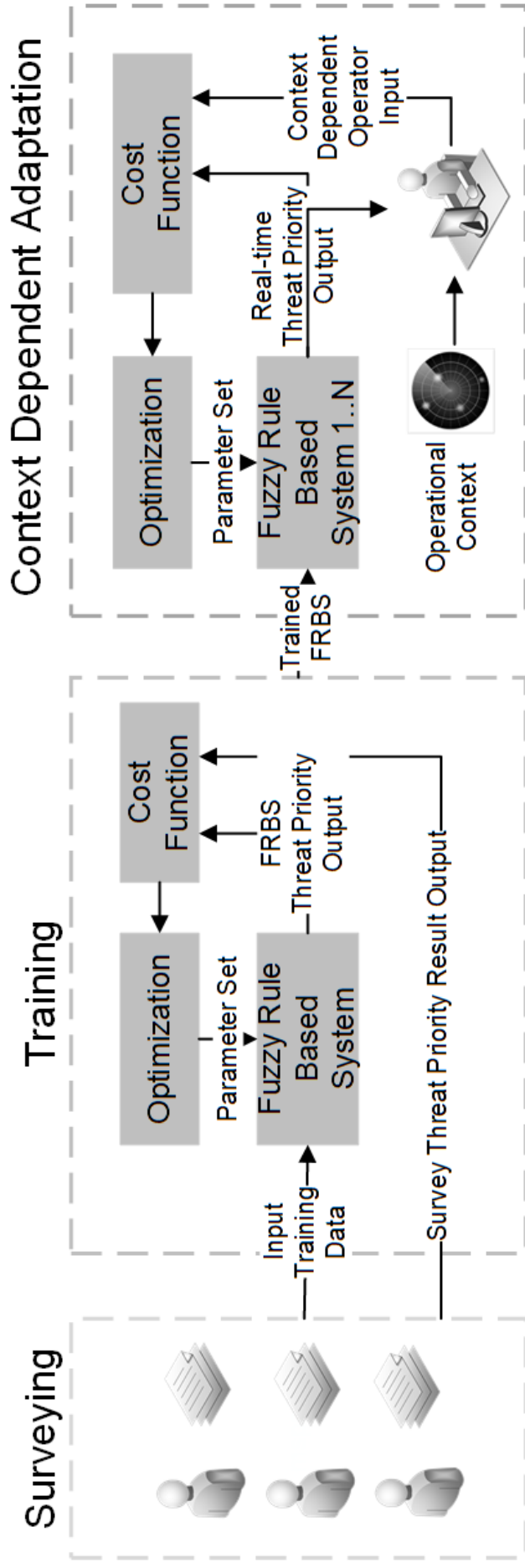


Figure 3.2 : Adaptive fuzzy-based threat evaluation system block diagram.

3.2 Use of Genetic Fuzzy Systems for Threat Evaluation Automation

GFS is a common adaptive approach to automate the definition of an FRBS. Proposed by Holland [98], GA is based on the concept of biological evolutionary processes. It is a derivative-free stochastic optimization approach where each point in solution space is encoded into chromosomes represented by a binary bit string. The fitness function used in GA is mapped to the objective function of the original problem. A set of chromosomes called a population representing possible solutions is generated initially. These chromosomes can be evolved by selection, crossover, and mutation operators. The capability of GA has attracted researchers to use it in the automatic learning of FRBS, which led to the development of GFS.

GFS is a hybrid approach combining fuzzy logic and GA to learn or tune FRBS rules and MFs. GAs ability to explore a large search space allows them to find suitable solutions for parameters of FRBS using apriori knowledge.

GFS approaches can be divided into two main processes: tuning and learning [99]. In the tuning process, existing KB is used, and a genetic tuning process is applied to improve FRBS performance while maintaining the rule base. However, in the learning process, KB components are learned using GA.

Genetic tuning can be divided into two main categories. In the first category, the KB that consists of a preliminary database (DB) and derived RB is used to adjust MF parameters. Shapes of the MFs are tuned while preserving the number of linguistic terms in each fuzzy partition. The second category is named genetic adaptive inference engine, in which either parameterized expressions in the inference system are used or a defuzzification function is applied to every inferred rule fuzzy set and computed by a weighted average operator.

On the other hand, genetic KB learning has four main categories. The first category, genetic rule learning, uses a predefined DB to learn the RB, as shown in Figure 3.3.

The second approach deals with the selection of rules to eliminate redundant, irrelevant, erroneous, or conflicting rules previously extracted by a rule extraction process. A combined approach that improves DB definition after RB's definition is

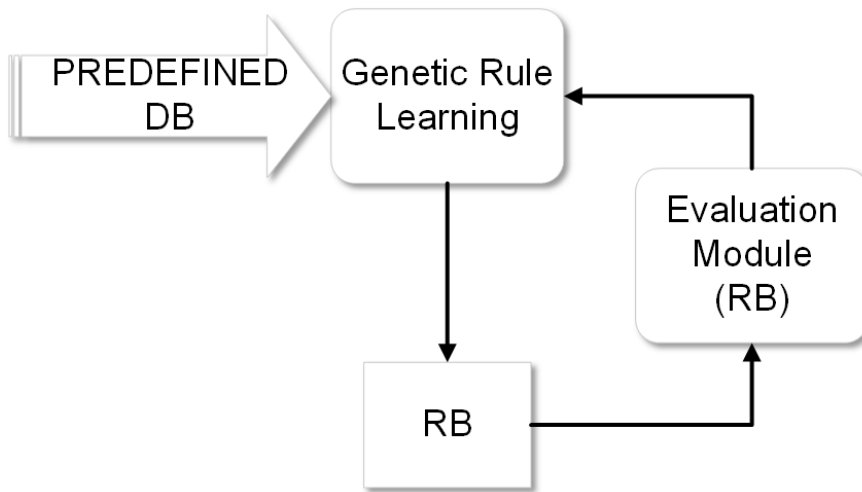


Figure 3.3 : Genetic RB learning.

also possible. Another approach shown in Figure 3.4 aims to learn both DB and RB components of KB simultaneously, providing better definition at the cost of slower convergence of the complex solution space.

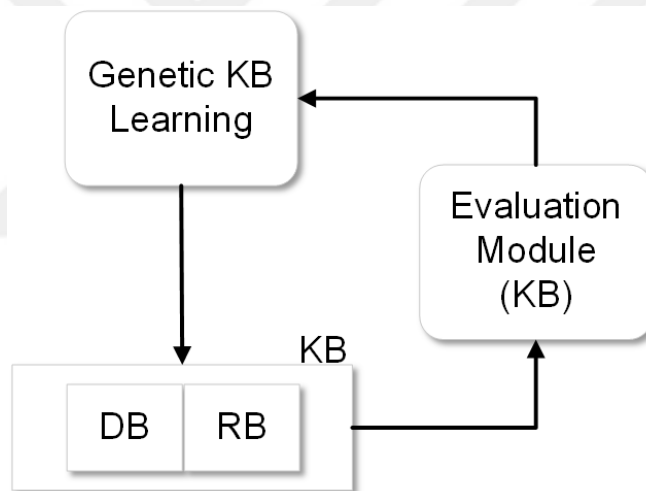


Figure 3.4 : Simultaneous genetic KB learning.

The last approach shown in Figure 3.5 encapsulates an RB generation process in a DB generation process. This process separates the solution space into simpler DB and RB solution spaces, enabling faster convergence than simultaneously learning KB components [100].

With the learning and tuning capabilities of GFS, they can be well utilized in the automation process of FRBS components in the ADS TE function.

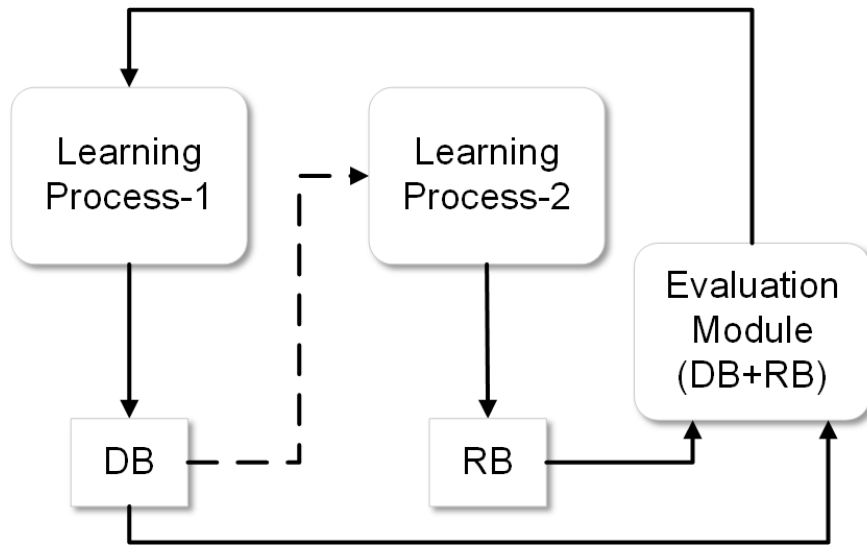


Figure 3.5 : RB Generation process encapsulated by DB generation process.

3.3 Proposed Adaptive Fuzzy Based Threat Evaluation System

The proposed adaptive fuzzy-based TE system will be explained sequentially, starting from the survey methodology through the training and context-dependent adaptation part of the system.

3.3.1 Survey methodology

A robust TE DSS system for ADS shall comply with expert air defense operator decisions when subjected to similar operational conditions. To design such DSS for TE, user knowledge from experienced operators shall be collected systematically. One way of collecting this information is the real-time observation of the operators for their actions and verbal descriptions when they are exposed to different kinds of scenarios composed of several vignettes in a simulated operational environment. Recording the operator behavior with a real or a prototype air defense console in different situations reveals an understanding of the cognitive factors affecting operator actions. An excellent example of such research is the TADMUS program carried out in the '90s, especially for naval air defense needs of the American Navy that appeared after the Gulf War [101]. The research program has led the way to understanding the cognitive factors of naval air defense operators, enabled TE models for DSS to be developed, and provided guidelines for displaying relevant threat information to air defense operators in a way to reduce the cognitive load in the stressful operational

context [102]. Being an extensive study, this research has been applied to a limited number of air defense operators and took several months to complete. Another way of collecting expert information is the application of surveys. These surveys aim to collect information on the operator's threat perception when faced with different situations. Application of these surveys does not need special hardware or software and can be applied to numerous air defense operators to increase the population size, hence the knowledge DB.

For surveying, different parameters affecting TE that are categorized as capability and intent shall be selected. The survey tries to answer the threat perception of the operator under different operational scenarios in which the capability and intent parameters of threat are varied. The survey contains various vignettes that an ADS operator can encounter. The operators are asked to select from discretized threat perception levels for each vignette. Table 3.1 shows the outline for the sample survey where input data are formed from the capability and intent parameters of the threat. Threat parameters such as hostility, speed, range to ADS, time to reach the Closest Point of Approach (CPA), distance to CPA, and range to the closest DA are filled with values in different rows corresponding to a specific vignette. The operator is asked to respond to each particular instance's perceived threat priority level.

Table 3.1 : Sample survey input and corresponding survey output.

Survey Input Data						Survey Output Data	
Hostility	Speed (m/s)	Range to ADS (m)	Time to Reach to CPA (s)	Distance to CPA (m)	Range to DA (m)	Threat Priority Response	
Hostile, Unknown or Friend	Speed of the target	Range of the target to ADS in meters	Time to reach the closest point of approach (CPA) of DA in seconds	Normal distance while passing through the DA in meters	The range to the closest DA in meters	Threat Perception Level Selected by the Operator	

Selection of threat perception level in survey output data varies from "Non-threat" meaning that with the given parameters, the operator concludes that the target does not create any threat to "Absolute threat" where the air defense operator is undoubtedly sure about the threatening behavior of the target. Possible choices for a nine-level selection and the description of each level are given in Table 3.2. Operators are instructed to select one of these options when faced with the conditions given in the vignette. The survey does not ask the operators to put some number in the corresponding scenario instance. This is done not to confuse them with numbers and allow them to think in linguistic variables, which are closer to the human way of thinking. The operator responses are mapped to numerical threat values for the subsequent training process. The mapping function can be a simple linear function as well as non-linear functions that can be obtained using different surveys, which ask operators to map these levels to numerical values in various operational modes.

Table 3.2 : Expected survey response for threat perception level of the operator.

Threat Perception Level	Description
Non-threat	The target does not create any threatening situation.
Extremely-Low	The target is perceived to be a little more than a non-threat situation.
Very-Low	The target is perceived as a non-threat with some doubt.
Medium-Low	The target's threatening behavior is slightly less than its non-threatening behavior.
Medium	Not sure about whether the target is hostile or not.
Medium-High	Threatening behavior is slightly more than non-threatening behavior.
Very-High	The target is perceived as a threat with some doubt.
Extremely-High	The target is perceived as a threat but with little doubt.
Absolute Threat	There is no doubt about the target's threatening situation.

3.3.2 Structure of the developed fuzzy rule-based system

After conducting the survey, the next step is to initialize the FRBS trained with the KB obtained from the survey result. FRBS input variables are formed from the survey input data parameters, and the output variable is the target priority. Initially, the rule base is empty, and GFS optimization will be used to extract the rules of the FRBS. FRBS input and output variables for the sample survey in Table 3.1 are also shown in Figure 3.6. For each of the fuzzy input variables, the linguistic terms and the

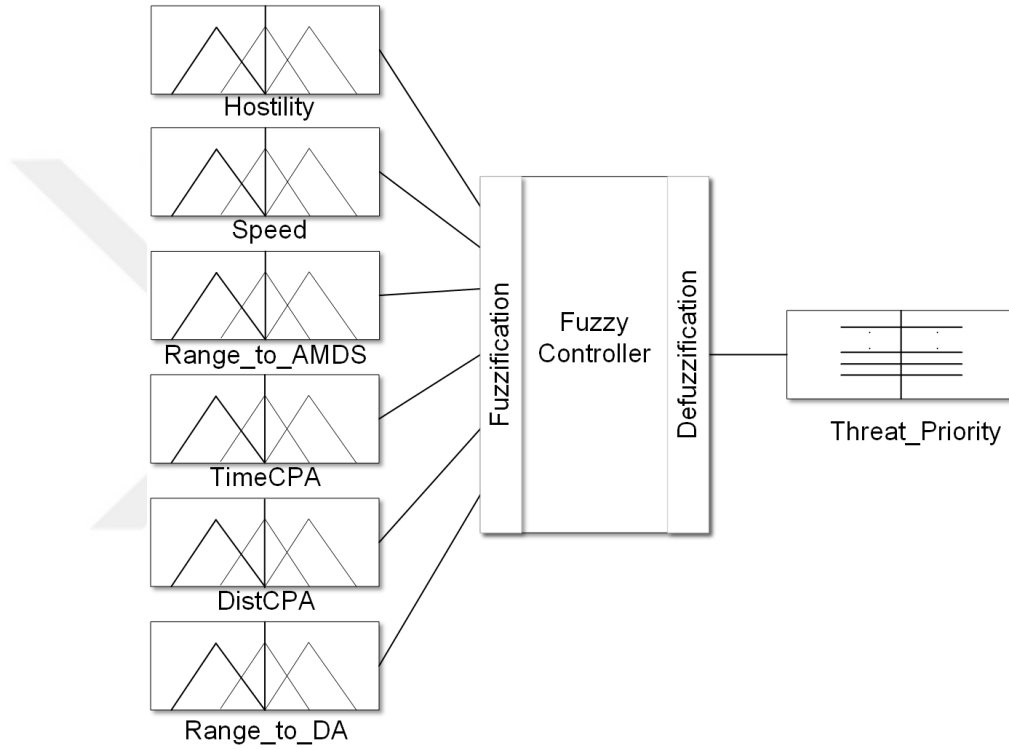


Figure 3.6 : Developed fuzzy rule base system.

interval consisting of the lower and the upper limits are set. Before the optimization process, an MF must be selected for each linguistic term for each fuzzy input variable. The selection of an MF also plays a vital role in the overall performance of FRBS representation. Various options are available for choosing MF, such as Gaussian, trapezoidal, triangular function, etc. Although there are some references on how to select an MF for a fuzzy rule-based system [103, 104], the selection of MF shape is dependent mainly on the nature of the problem. In general, Gaussian and triangular MFs are shown to be performing better than other types of MFs. Triangular MF is frequently used because of its simplicity and faster computation speed [105]. It has

also been shown in the literature that triangular MF performs better than other types of MFs in control applications [106]. For our threat evaluation system application, the overall system shall work in real-time; hence, computation speed is our initial concern. For this study, triangular MFs are selected for input variables in view of the literature while still considering the benefit of choosing different MFs, such as Gaussian, on the overall system's performance at the expense of computation speed.

Selection of the inference method for FRBS is also essential. There are four types of inference methods called with their founders: Mamdani [107], Takagi-Sugeno [108], Larsen [109] and Tsukamoto [110]. Among those methods, Mamdani and Takagi-Sugeno are widely used in the field of fuzzy control. Mamdani systems are well suited to human input, intuitive, and have a more interpretable rule base; however, Takagi-Sugeno systems are computationally efficient and work well with optimization and adaptive techniques. Both have different advantages; one shall select the type of FRBS to be used according to the kind of application. For our application, to get better optimization results with a lower computation cost considering a real-time operation, Takagi-Sugeno type FRBS is chosen.

The typical output of a Takagi-Sugeno type FRBS can be represented as:

$$\text{if } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = f(x, y)$$

where A and B are fuzzy sets in the antecedent, $z = f(x, y)$ being a crisp function in the consequent, the fuzzy inference system is called a first-order Sugeno fuzzy model when $f(x, y)$ is a first-order polynomial. If function f is constant, the resulting inference system is a zero-order Sugeno fuzzy model. The zero-order Sugeno fuzzy mode is selected for this study, and the selection of the zero-order Sugeno model for our application is twofold. It is known that as long as the neighboring MFs in the antecedent have enough overlap, the output of a zero-order Sugeno model is a smooth function of its input variables. [111]. In addition to this, as the order of the Sugeno model increases, the computation cost increases. Considering real-time operation in the context-dependent adaptation process of the TE system, a zero-order Sugeno model is selected for the FRBS output. Developed FRBS has no rules at the initialization stage. The rules will be extracted in the subsequent training process.

3.3.3 Training and context-dependent adaptive FRBS tuning processes

After surveying air defense operators, DB is collected from the answers given to specific threat vignettes and consequent numerical mapping of linguistic terms such as hostility and threat priority. This DB will be used as input data in the training process of the FRBS generation part of the TE DSS system to find the RB and optimize MFs. The training process is followed by a context-dependent adaptive tuning process where the fuzzy system is tuned by operators with real-time input experience gained from new operational situations. The processes of the proposed solution to the problem are described in the following subsections.

3.3.4 Training process

The training process utilizes survey results as a DB for automatic FRBS generation. This part of the algorithm uses GFS, which tries to minimize the pre-defined cost function between the input data and the expected threat priority output of the survey result. The training process consists of two consecutive phases, as shown in Figure 3.7. In the first phase, the rules of the FRBS are formed using GFS; in the second phase, the MFs and rule base are optimized also using GFS.

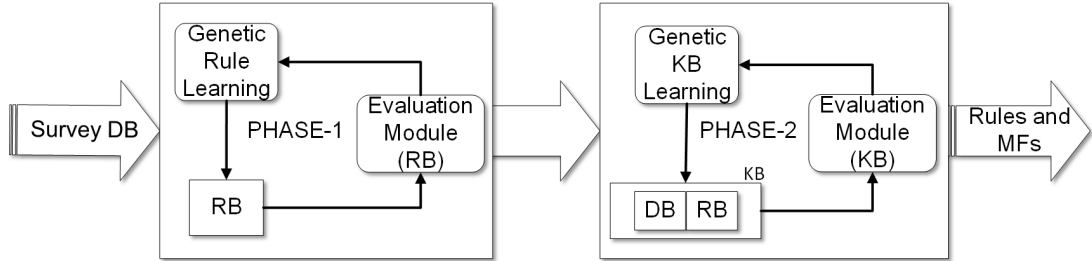


Figure 3.7 : Training process phases.

In each phase, GFS minimizes a cost function, as shown in Figure 3.8. Root Mean Square Error (RMSE) cost function is used as a distance metric in the training process of the proposed method, which is taken as;

$$RMSE = \sqrt{\sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (3.1)$$

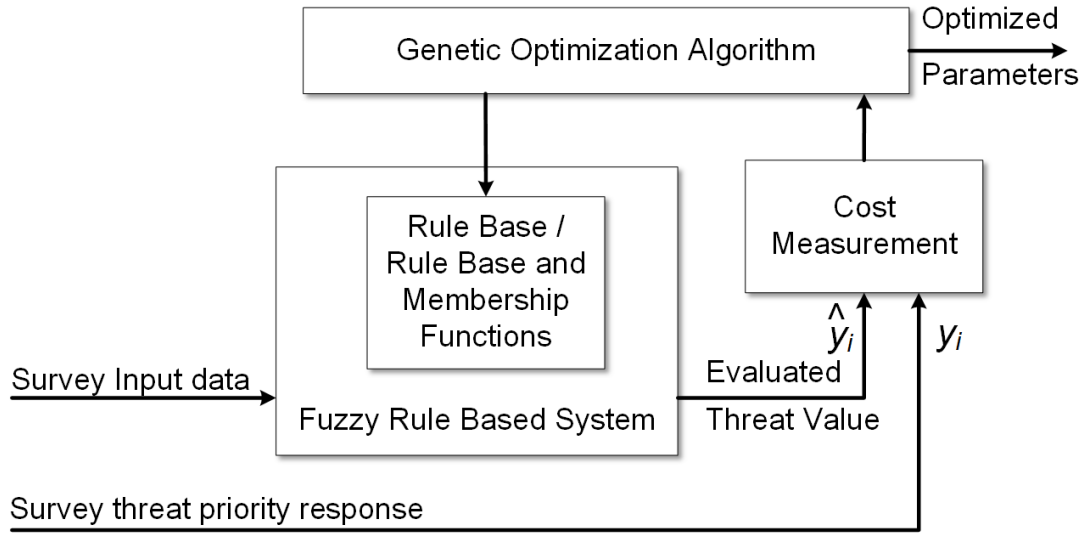


Figure 3.8 : Genetic fuzzy optimization block diagram.

where $\hat{y}_i$ is the fuzzy system evaluated threat value, y_i is the survey threat response result value, and n is the number of training samples, which is the number of survey questions that experts have responded. Training phases will be described respectively in the following paragraphs.

3.3.4.1 Training process: phase-1

In the first phase of the training process, the rules of the FRBS are extracted from the DB using GFS. The number of rules of this optimization process is an important parameter that has to be selected during the training process. Assigning a low number of rules in the training optimization process will output an FRBS that does not reflect the operator's behavior. On the other hand, utilizing many rules will not only extend the training optimization time but also extend the context-dependent adaptation duration of FRBS to the different operational contexts in the subsequent tuning process. The number of rules can be optimized as a trade-off between accuracy and speed needed for the application. A predefined RMSE threshold can be selected to find the optimum number of rules, and the number of rules can be increased until the point where the RMSE metric target is obtained.

Table 3.3 shows the expected rule output from the optimization in Phase-1 of the training process where k_1 and k_2 are constant Sugeno zero-order outputs.

Table 3.3 : Generated fuzzy logic ruleset in Phase-1 of training process.

Rule	Hostility	Speed	Range_to_ADS	TimeCPA	DistCPA	Range_to_DA	Threat Priority
#1	Friend	Fast	Any	Low	Low	Low	k1
#2	Friend	Slow or Medium	Low	Any	Any	Low	k2
:	:	:	:	:	:	:	:

3.3.4.2 Training process: phase-2

After the first phase, the output of the threat priority of the trained FRBS is compared with the original responses of the survey with a predefined threshold to obtain a reduced data set. In the second phase, both DB consisting of the MFs and the rule base are optimized simultaneously with this reduced data set. The upper and lower limits for the input MFs of those stated variables are given before the optimization. The triangular function used in the FRBS and the equation for the function are shown in Figure 3.9.

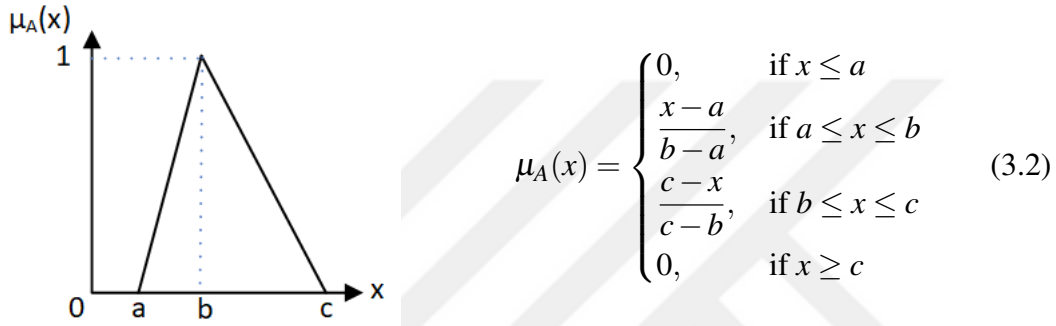


Figure 3.9 : Triangular membership function.

The MF can be described more compactly as:

$$\mu_A(x) = \max(\min(\frac{x-a}{b-a}, \frac{c-x}{c-b}), 0) \quad (3.3)$$

Parameter a is the lower boundary of the membership function, b is the center where the membership degree is one, and c is the lower boundary of the MF. The a, b, and c parameters are variables of MF that will be optimized using GFS during the second phase of the training process, as shown in Figure 3.10. There will be as many MFs for each vague value that a variable can take. The output of the second phase of the training process is an FRBS with an optimized ruleset and optimized parameters for the MFs. The training process is offline and can be run before ADS has been deployed. Also, as the threat environment changes, if the operators utilizing the system give feedback that the TE system fails to reflect the changed threat perception anymore, the offline training process can be repeated after ADS deployment with the collection of new KB through updated surveys. The output of the FRBS will be the target priority that

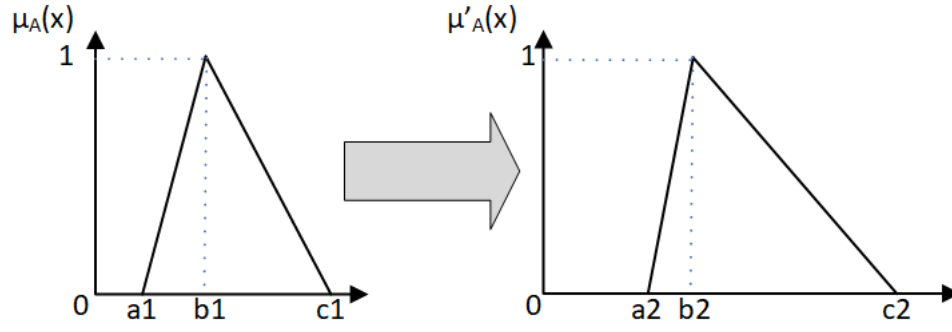


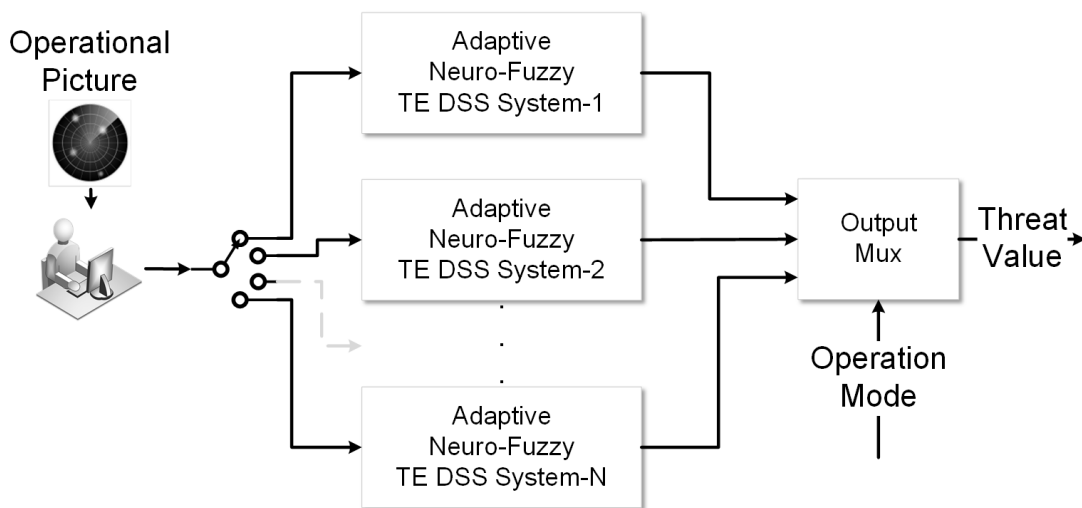
Figure 3.10 : Membership function optimization in the second phase.

will support the operator in the decision process and will also be input to the weapon assignment function of ADS.

3.3.5 Context dependent adaptation process

After the training process, FRBS, which will form the core of the TE DSS system, is created. As stated before, the ADS system shall operate in different operational contexts such as peacetime, crisis, or wartime. These different operational contexts affect the operator's decisions while evaluating the threat degree. The solution to this problem can be overcome by using multiple FRBS running for each operational context and using the output of related FRBS for the TE DSS. Either these FRBS can be the output of different training processes of the answers of the operators collected for each operational context that they will be in, or they can be a local copy of the trained FRBS from the survey responses for a single operational context, i.e., peacetime operation. These local copies will be tuned by the operator input during the simulation mode of ADS or during operational scenarios faced in actual system operation. Figure 3.11 shows the application of the latter idea, which we call the Context-Dependent Adaptive FRBS Tuning Process.

The tuning process assumes the initial rules to be kept as they are created in the training process. This process aims to tune the MFs to adapt to different operational contexts. Since there will be fewer variables to be optimized than the training process, real-time application of the tuning process is more feasible than the training part. In the next section, numerical performance results are given to demonstrate the effectiveness of the proposed method.



3.4 Numerical Performance Results

To investigate the proposed adaptive fuzzy-based TE system solution, a sample survey has been conducted on two groups of operators with more than five years of experience in the field. The selection of experienced operators for the survey reduces any inconsistency in constructing the experimental sample. The aim is to understand whether starting from a survey study, it is possible to acquire user knowledge in a fuzzy system by using adaptive fuzzy systems and possibly adapting it to real-time operation. There are 500 different questions asked for each participant in the groups. A simple scenario shown in Figure 3.12 is built up that consists of a DA and an ADS protecting this asset. The scenario does not contain any map to avoid influencing operator choices that may be affected by the geographical context. In our study, sample intent parameters of threat are selected for the survey since they are more subjective amongst experts rather than capability parameters. These parameters have been chosen for the fuzzy system to solve the problem. Parameters used in the survey are listed with a brief description in Table 3.4.

Vignettes are visualized and simulated according to target approach routes, and the operators are asked to answer their feelings about the situation. The answers are recorded in a spreadsheet. Table 3.5 shows sample responses of operators according to the scenario. As seen from the first row of the sample responses, the operator

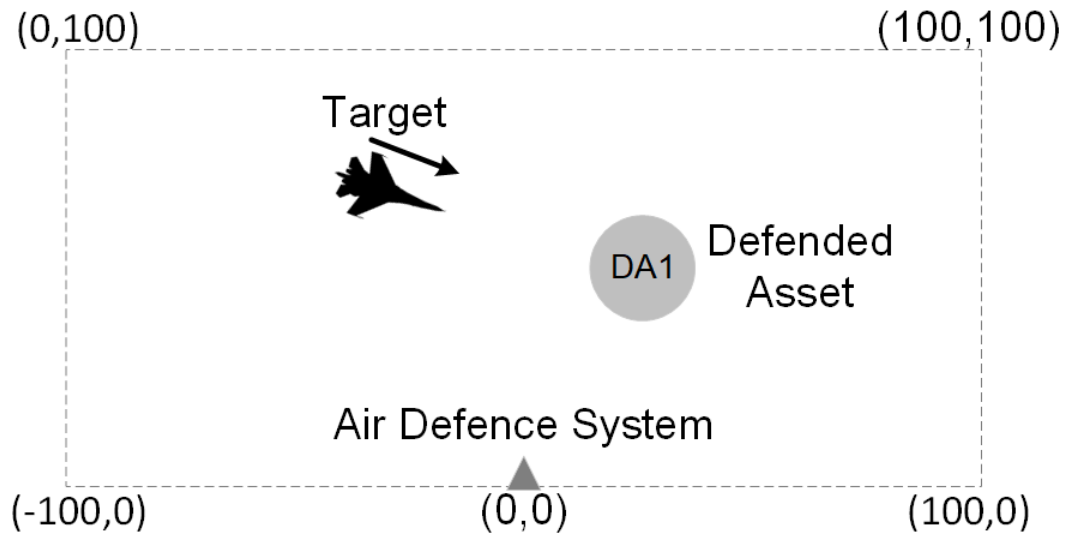


Figure 3.12 : Scenario used in the survey study.

Table 3.4 : Survey input parameters and descriptions.

Parameter	Description
Hostility	The options are Hostile, Unknown, and Friend
Speed	Speed is measured in meters per second
Range to ADS	Range of the target to ADS in meters
Time to CPA	Time to reach the closest point of approach to DA in seconds
Distance to CPA	Normal distance while passing through the DA in meters
Range to DA	The range to the closest DA in meters

labeled the target as an "Extremely-High" threat. At first glance, it seems that the operator looks at the target range to ADS, the remaining time to the closest point of approach, and the distance to it and values it accordingly. However, in the second row, although range to ADS and CPA values are high, the operator also labels it as an "Extremely-High" threat. The difference is the target's speed; it can be seen from the table that the target is moving supersonic and labeled as "Hostile" in the identification process of ADS. In the fourth response, the operator stays between a threat and a non-threat perception when the distance to DA is high, but the target is close to

ADS. Lastly, two answers indicate that the operator tends to choose a low threat value when the threat is labeled as "Friend" in the identification process regardless of other parameter values.



Table 3.5 : Sample input data and corresponding survey output (threat priority response).

Hostility	Survey Input Data					Survey Output Data	
	Speed (m/s)	Range to ADS (m)	TimeCPA (s)	DistCPA (m)	Range to DA (m)	Threat Priority Response	
Friend	208	2232	57	2000	79387	Extremely-High	
Friend	358	118319	558	726	186342	Extremely-High	
Friend	393	3916	492	805251	131435	Extremely-High	
Friend	262	10582	296	505936	217544	Medium	
Hostile	248	3742	644	935798	125099	Very-Low	
Hostile	114	64030	528	629305	235503	Extremely-Low	

An initial training study has shown that there should be enough data for each expected answer to have a better model fit. Looking at the initial responses, the threat degree is responded low when the "Hostility" input of the survey is "Friend". If the "Friend" ratio is uniform for all the questions, it has been understood that we will not get enough data for cases where we expect a higher threat level. The questions are systematically randomized to have an almost equal sample from each expected answer before surveying to get a meaningful distribution. After randomizing, a second subsampling operation is performed to equalize the number of responses from each threat priority response output.

After collecting the survey data, the linguistic variables are mapped to numerical threat levels to prepare data for the training process. Although there are other possibilities for mapping the answers to a threat degree, linear mapping is used as the expected threat degree output. The increments for the linear mapping are 0.125, and the threat value is represented by 0 for the "Non-threat" case and 1 for the "Absolute Threat" case for our study. The hostility input parameter is mapped to discrete values of 0 for friend, 0.5 for unknown, and 1 for hostile.

FRBS variables to be trained using GFS and their linguistic terms are shown in Table 5.1. In this study, three MFs for each of the six input variables are selected. Input membership functions for "Hostility" and "Range to DA" fuzzy variables are shown as examples in Figure 3.13. Three triangular MF are defined with initial parameters for each fuzzy input variable defined in Table 5.1. The output MF of the generated Takagi-Sugeno type FRBS is initialized with linear increments from 0 to 1.

Table 3.6 : Fuzzy rule-based system variables.

Parameter	Value
Hostility	Friend, Unknown, Hostile
Speed	Slow, Medium, Fast
Range to ADS	Low, Medium, High
Time to CPA	Low, Medium, High
Distance to CPA	Low, Medium, High
Range to DA	Low, Medium, High

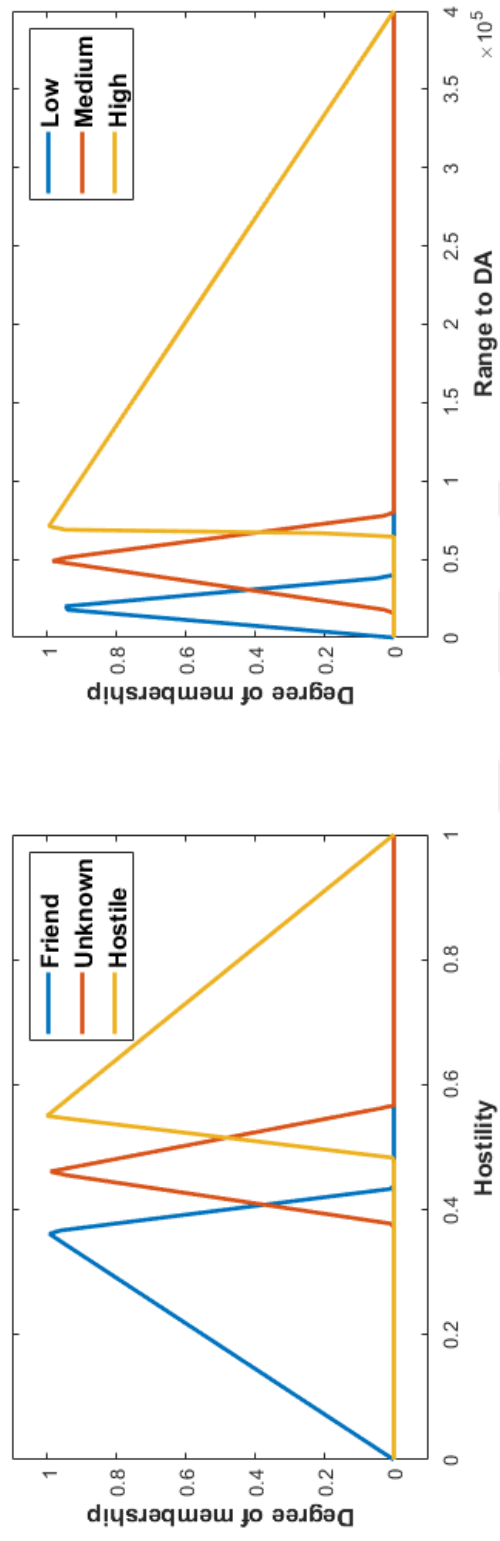


Figure 3.13 : Input membership functions for hostility to ADS and range to DA.

The genetic algorithm in Matlab R2022a global optimization toolbox was used to train FRBS using GFS. For the fitness scaling function, the "fitscalingprop" option is selected to make the scaled value of an individual proportional to its raw fitness score. The stopping conditions for the GA are selected by the "MaxStallGenerations" and "MaxGenerations" options. "MaxStallGenerations" value determines the stopping condition of the algorithm if the average relative change in the best fitness function value over "MaxStallGenerations" is less than or equal to "FunctionTolerance". The default value $1e-6$ is used for "FunctionTolerance" and 50 is selected for the "MaxStallGenerations" option. The maximum number of iterations defined by the "MaxGenerations" option is selected as 150 for our application. All other options are kept at default values for genetic optimization. Table 3.7 lists the parameters of the genetic optimization algorithm used in the numerical performance analysis.

Table 3.7 : Genetic optimization algorithm parameters.

Parameter Name	Value
Max Generations	150
Max Stall Generations	50
Population Size	1200
CrossoverProbability	0.8
Fitness Scaling Function	@fitscalingprop
Selection Function	@selectiontournament
Mutation Function	@mutationadaptfeasible
Function Tolerance	$1e-6$

Phase 1 of the training process extracts the ruleset of the FRBS through genetic optimization. Reference FRBS is fed to the optimization algorithm with the training data collected through survey results. Table 5.2 shows sample extracted rules and assigned output threat priority results.

Table 3.8 : Generated sample fuzzy logic ruleset in Phase-1 of training process.

Rule	Hostility	Speed	Range_to_ADS	TimeCPA	DistCPA	Range_to_DA	Threat Priority
#1	Hostile	Fast	Medium	Medium	Any	Medium	0,7844
#2	Hostile	Medium	Medium	Medium	Medium	Medium	0,7308
#3	Friend	Fast	Low	Medium	Any	Medium	0,3405
#4	Unknown	Fast	Medium	High	Medium	High	0,3405
#5	Friend	Slow	Medium	Medium	Low	High	0,0618
:	:	:	:	:	:	:	:
#55	Unknown	Fast	Medium	Any	Any	Any	0,3405
#56	Unknown	Fast	Medium	High	Medium	High	0,3405
#57	Friend	Slow	Medium	Medium	Low	Medium	0,0618
:	:	:	:	:	:	:	:
#143	Hostile	Slow	High	Medium	Low	Medium	0,4434
#144	Unknown	Any	Low	Medium	Low	Medium	0,6578
#145	Any	Medium	Any	Low	Low	Low	0,7308

Phase 2 of the training process optimizes both MF parameters and the rule bases extracted in Phase 1. The updated MFs for the sample fuzzy variables "Hostility" and "Range to DA" are shown in Figure 3.14. As can be seen through the graphs, the triangular MF parameters are slightly changed by genetic optimization to fit the training data better. Initial MF parameter values for sample fuzzy variables "Hostility" and "Range to DA" and parameter values after optimization are shown in Tables 3.9 and 3.10 respectively. Shared rules of Phase-1 and Phase-2 of the training process shown in Table 3.11 indicate that the output threat priority result for Rule#2 is changed to reduce the RMSE of the training data and FRBS output. Table 3.11 indicates that operator expectation for threat priority is Very-High when the Hostility fuzzy variable is hostile and the speed of the target is fast (Rule#1), whereas threat priority is at the lowest level when the target is a friend with a slow speed which is far away from DAs (Rule#5). Observations on the ruleset and associated threat priority result confirm the efficiency of the proposed Adaptive Fuzzy Based Threat Evaluation System.

Table 3.9 : Input and optimized parameters for hostility MF.

Name	Input MF Parameters			Optimized MF Parameters		
	a	b	c	a	b	c
Friend	0	0.364	0.434	0	0.364	0.434
Unknown	0.377	0.46	0.5663	0.39737	0.48066	0.55705
Hostile	0.483	0.5498	1	0.48252	0.64004	1

Table 3.10 : Input and optimized parameters for range_to_DA MF.

Name	Input MF Parameters			Optimized MF Parameters		
	a	b	c	a	b	c
Low	0	18910	38800	0	18910	38800
Medium	16900	49420	78600	12948	32630	77514
High	66050	69050	4e+05	52176	70707	3.9998e+05

Table 3.11 : Updated sample fuzzy logic ruleset in Phase-2 of training process.

Rule	Hostility	Speed	Range_to_ADS	TimeCPA	DistCPA	Range_to_DA	Threat Priority
#1	Hostile	Fast	Medium	Medium	Any	Medium	0,7844
#2	Hostile	Medium	Medium	Medium	Medium	Medium	0,7391
#3	Friend	Fast	Low	Medium	Any	Medium	0,3405
#4	Unknown	Fast	Medium	High	Medium	High	0,3405
#5	Friend	Slow	Medium	Medium	Low	High	0,0618
:	:	:	:	:	:	:	:
#55	Unknown	Fast	Medium	Any	Any	Any	0,3405
#56	Any	Fast	Medium	High	Medium	High	0,3405
#57	Friend	Slow	Medium	Medium	Low	Medium	0,0618
:	:	:	:	:	:	:	:
#143	Hostile	Slow	High	Medium	Low	Medium	0,4434
#144	Any	Any	Low	Medium	Low	Medium	0,7391
#145	Any	Medium	Any	Low	Low	Low	0,7844

RMSE results for the first and second phases of the training process are shown in Figure 3.15. The figure shows RMSE for each threat priority level after the initial training phase and consequent second phase. As shown from Figure 3.15, lower threat priority categories are optimized well in the second phase; however, RMSE values for very high threat priority categories were increased.



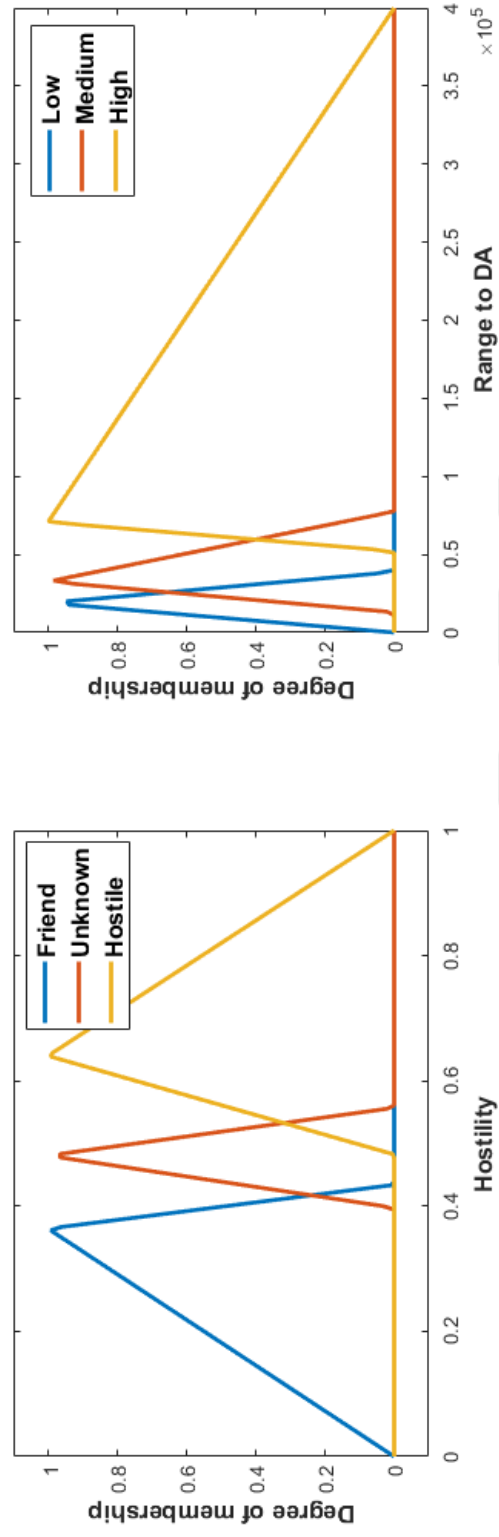


Figure 3.14 : Optimized input membership functions for hostility and range to DA.

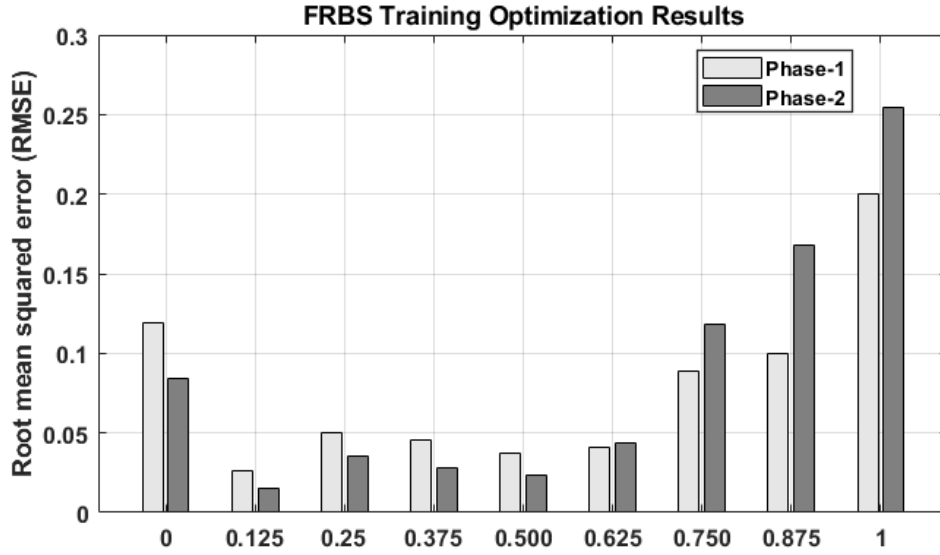


Figure 3.15 : Phase-1 and Phase-2 RMSE results.

For the ADS TE DSS system, incorrect estimation of the threat priority may result in not engaging more threatening targets or, on the contrary, engaging lower-priority targets. However, obtaining less error for higher threat priority estimates is more important. To get a lower error for targets with a higher threatening degree, the cost for assessing a lower value to a higher threatening threat shall be higher than assessing a higher threat value to a less threatening target. Therefore, a custom cost function is used in the fitness function of the genetic optimization, which boosts RMSE for higher threat priorities. The fitness function representing the modified cost is calculated for each threat priority category. The cost increases exponentially after the mid-threat priority category, which is 0.5 for the linear threat priority mapping to reduce RMSE for higher target threat priority results.

The fitness function f_c for each threat priority category c is defined as;

$$f_c = \sum_{c=1}^9 \left(\sqrt{\sum_{i=1}^{n_c} (\hat{y}_i - y_i)^2} \right) g(c) \quad (3.4)$$

where $g(c)$ is defined as;

$$g(c) = \begin{cases} e^{(c-mid_index)} & c > mid_index \\ 1, & otherwise \end{cases} \quad (3.5)$$

and n_c being the number of samples for each category.

The mid index in the linear mapping is five, corresponding to the threat priority level of 0.5, and the cost increases for the categories above mid-level. The resultant RMSE for the optimization output is shown in Figure 3.16. As can be seen from the figure, the RMSE value for the higher threat priority category decreases at the expense of a slight increase in threat priority estimations for lower threat priority categories when the custom cost function is used.

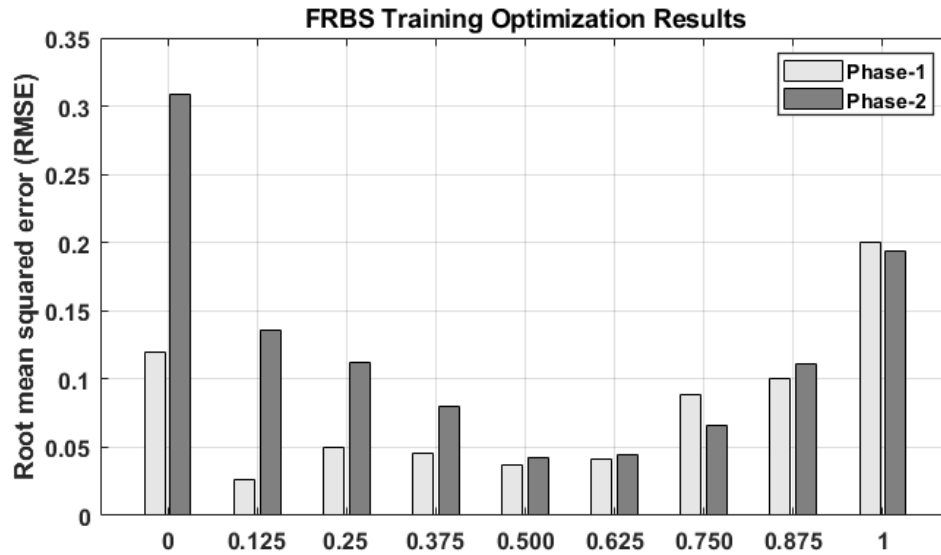


Figure 3.16 : Phase-1 and Phase-2 RMSE results with a custom cost function.

Operator responses during peace and war modes shall be obtained to test the context-dependent adaptation of FRBS that will be used in the TE DSS system. In peace mode, operators tend to give a lower threat priority level, while in war mode, the operators increase the level of threat they perceive. Keeping this in mind, instead of running a survey and obtaining operator responses for each operational context, operator responses for the normal case are modified using the threat priority mapping functions shown in Figure 3.17.

The survey threat priority response output is modified with the mapping functions, and genetic fuzzy tuning is applied to the FRBS obtained in the training process. Threat priority results and corresponding adjusted FRBS priority output are ordered from lowest priority to highest priority to understand the impact of context. The figure shows the normal output and the corresponding context-based tuned output in the same figure. As seen from Figure 3.18, threat priority results are shifted below, which is the expected behavior in peace mode operation.

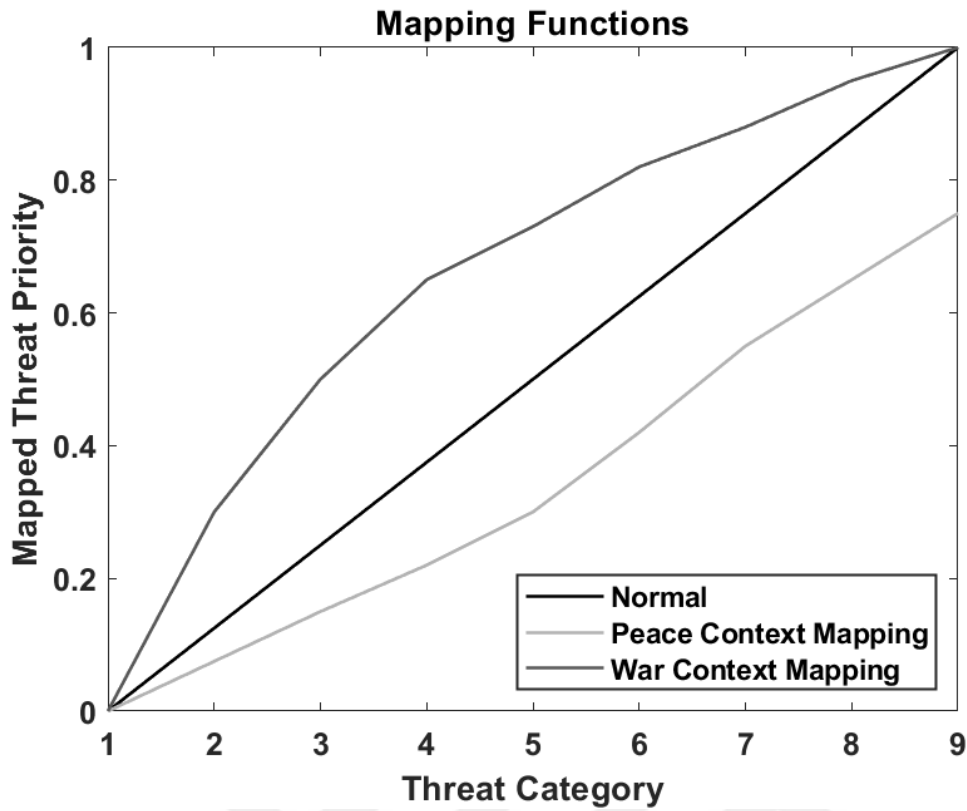


Figure 3.17 : Mapping functions used for context-dependent tuning.

Secondly, the survey results are modified with the war context mapping function, and a genetic fuzzy-based tuning is applied to the initially trained FRBS. The result is shown in Figure 3.19. As expected, the threat priority output of tuned FRBS is shifted up, reflecting operator behavior during this operational context. These figures show that the TE system can adapt to the context using different trained FRBSs. These FRBS can also be tuned by user input in different operational scenarios during operation.

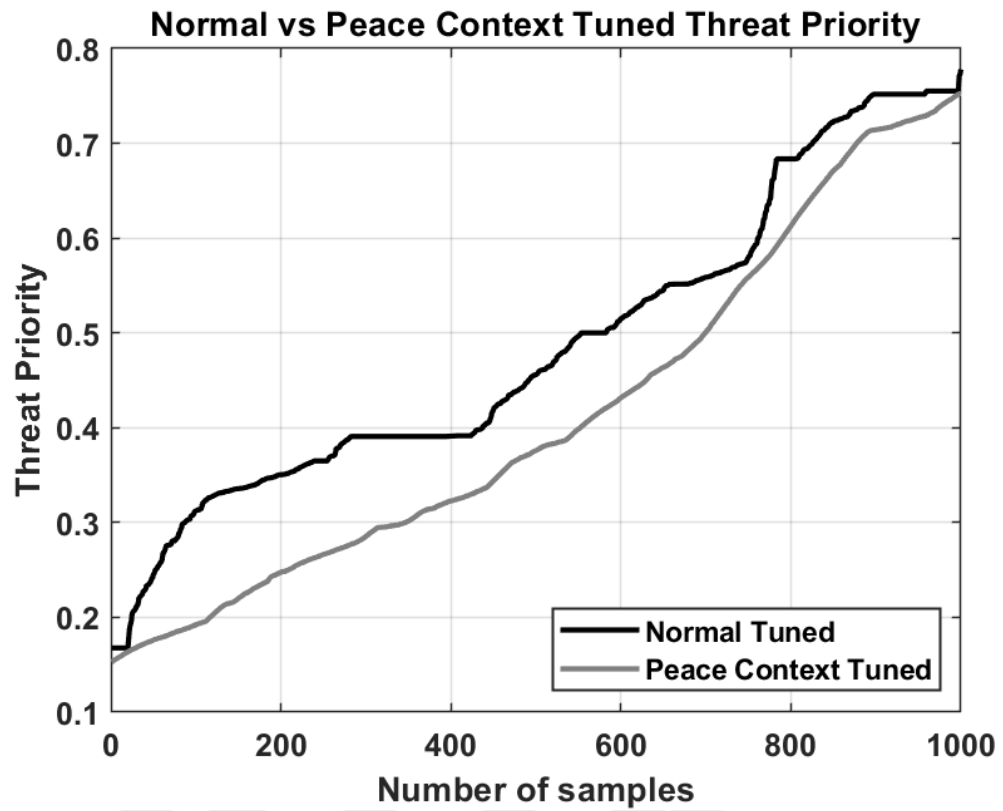


Figure 3.18 : Peace context tuning result.

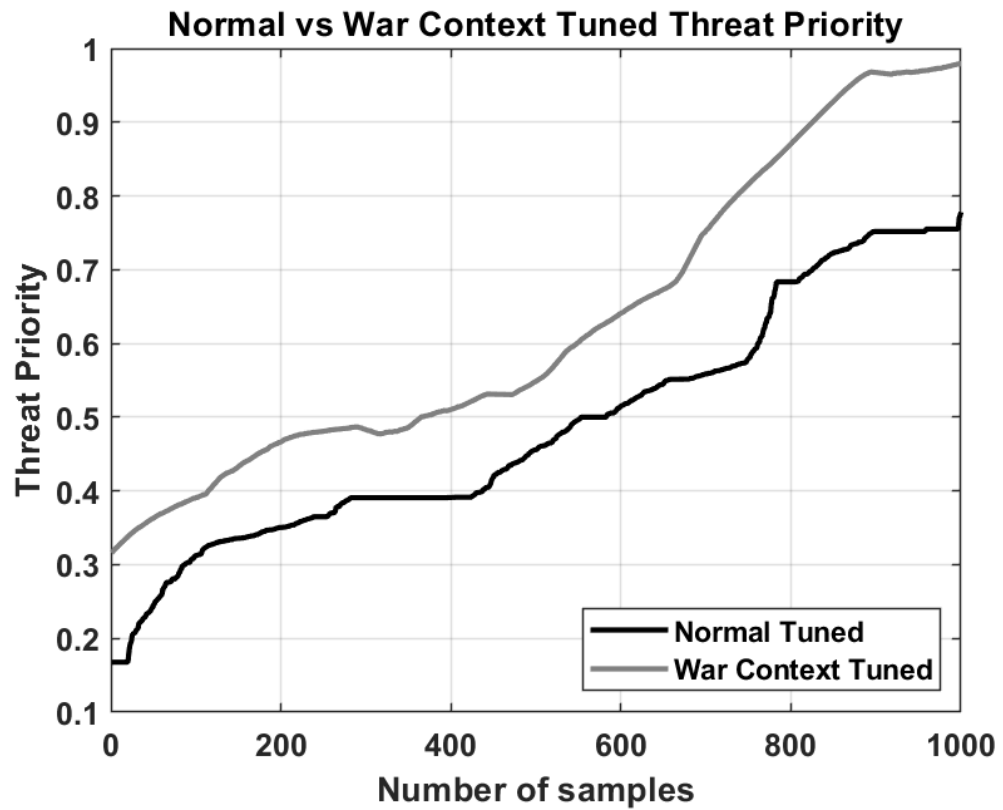


Figure 3.19 : War context tuning result.

3.5 Summary and Discussion

In this chapter, an application of an adaptive genetic fuzzy-based TE DSS for ADS application that starts with a surveying process where a knowledge base is collected from air defense operators via threat priority perception in different operational scenarios is proposed. As the second step, an offline training process is applied where the rules and parameters of the FRBS that will be used during ADS operation are optimized. A real-time adaptive context-based TE DSS system utilizing several trained adaptive fuzzy systems is proposed where the DSS system can also adapt itself to the operational environment via user input. In training and tuning processes, the GA-based optimization method with RMSE cost function is used to fit the fuzzy system model either to survey responses in the training mode or to real-time user input in the tuning process. In order to show the applicability of the proposed method, a sample survey is conducted with two groups of air defense operators. Using the survey results, numerical analysis results are given for the GFS-based optimization process with standard and custom cost functions, and context-dependent adaptation of FRBS for peace and war mode has been shown. Apart from the usage of conventional RMSE cost function, a customized cost function can be utilized in the optimization process to emphasize the cost for higher threat priority output errors. Optimization results with standard cost function have shown that for threat priority levels below medium-high, RMSE is below 0.1 and below 0.26 for higher threat priority levels. Utilizing the custom cost function resulted in decreased RMSE for higher threat priority levels at the cost of an increase in lower threat priority levels. As a future work, the effect of FRBS MF, i.e., Gaussian MF, on the GFS optimization process shall be studied, as well as the encapsulation of the RB generation process with a DB generation process to improve the training time of the FRBS generation process.

4. RESOURCE MANAGEMENT OF NETWORKED AIR DEFENSE RADARS USING ADAPTIVE TRACKING

4.1 RRM For Networked Air Defense Radars Using Adaptive Tracking

In air defense scenarios, targets approach the protected zone with a constant velocity straight route and tend to maneuver while it is tracked by FCR. In target tracking applications, the tracking accuracy degrades with target maneuvers since the measurements and resulting track updates are not enough to predict the actual trajectory of the target. The problem can be solved by increasing the measurement rate and, consequently, track updates to maintain the track accuracy at a specified level. On the other hand, during the straight flight path of the target, it is not necessary to update the track frequently to satisfy the required tracking accuracy. Increasing the measurement rate in order to cover the maneuvering portion of the flight unnecessarily utilizes radar resources for the straight flight portion of the targets.

The beam agility of MPAR allows adaptive update of the targets by increasing the measurement rate at the maneuvering portion and decreasing the measurement rate at the straight line portion of the flight. This capability, which uses adaptive update time intervals for target state estimation, is named adaptive tracking and frees radar resources for other radar functions. With the use of adaptive tracking, the tracking accuracy can be maintained by adjusting the measurement rate at different portions of the target flight path [112, 113].

Adaptive tracking can be extended to networked radars, where adaptive target update tasks are distributed to multiple radar nodes to manage the network resources. In the next section, a networked radar resource management algorithm will be described that aims to exploit the effect of utilization of target priority as well as target maneuver to adaptively track targets in a networked ADS whose Fire Control Radars (FCRs) are cooperating compared to previous studies that utilize only target priority [30] or target maneuver [114] for radar resource management.

4.2 Proposed Adaptive Update Rate RRM Algorithm for Networked Phased Array Fire Control Radars

Targets with a priority greater than a predetermined threshold and within reach of the interceptor kill box are engaged by the networked ADS. Also, as stated before, targets within the vicinity of the air defense system or locked by the FCR tend to maneuver. Other low-priority or non-maneuvering targets can be tracked less frequently to save FCR radar resources. Using this information, a resource management algorithm that utilizes adaptive target tracking based on the target priority and maneuver of the targets is proposed for networked ADS utilizing FCRs. The target prioritization and maneuver detection part of the algorithm will be described briefly, followed by a subsection that explains how adaptive tracking and radar task management are performed in the networked ADS according to these features.

4.2.1 Target prioritization

The algorithm utilizes FRBS to continuously calculate target priorities monitored against a predefined threshold level to trigger engagement tracking rates.

FRBS consists of three main steps: fuzzification, inference, and defuzzification. The fuzzification step determines the degree of the inputs belonging to each of the appropriate fuzzy sets via membership functions. Although different possibilities exist for choosing an MF type, triangular MF is widely used because of its implementation simplicity and computation speed [105]. In the proposed algorithm, triangular membership functions, as shown in Figure 3.9, are used for input and output variables. The inference process is used to derive a conclusion based on a set of if-then rules. The rules of the FRBS for an n input variable are formed as

$$\begin{aligned} & \text{IF } X_1 \text{ is } \tilde{A}_1^k \text{ AND } X_2 \text{ is } \tilde{A}_2^k \text{ AND } \dots X_n \text{ is } \tilde{A}_n^k \\ & \text{THEN } y \text{ is } \tilde{B}^k \text{ for } k = 1, 2, \dots, r \end{aligned} \quad (4.1)$$

where X_k ($k = 1, 2, \dots, n$) are input variables and y is the output variable. The maximum number of rules for the ruleset is $r = p^n$, where p is the number of linguistic terms corresponding to each input variable. $A_1^k, A_2^k, \dots, A_n^k$ are the linguistic terms used for

the corresponding input membership functions, and B^k are the linguistic terms used for the output variable for the k th rule.

The Mamdani inference method [107] is used in the proposed FRBS. For the rules of more than one input variable, fuzzy set operations are applied to obtain a final membership result. After this calculation, the *min* implication method is used to find each rule's conclusion. Finally, the output from each rule is combined using a fuzzy aggregation *max* operator.

The Mamdani inference method is formulated as follows;

$$\mu_{\tilde{B}}^k(y) = \max_k \left[\min \left[\mu_{\tilde{A}_1}^k(X_1), \mu_{\tilde{A}_2}^k(X_2), \dots, \mu_{\tilde{A}_n}^k(X_n) \right] \right] \quad (4.2)$$

for $k = 1, 2, \dots, r$ number of distinctive rules with X_i ($i = 1, 2, \dots, n$) input variables.

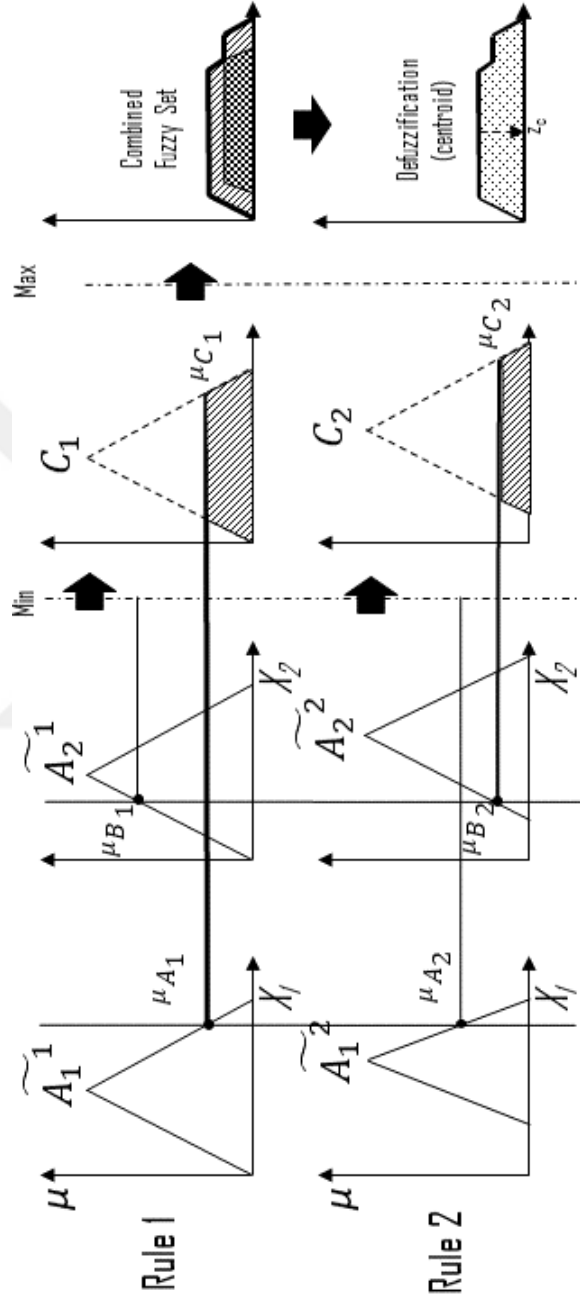
The last step of the FRBS is the defuzzification step. The defuzzification process combines the output from all rules to generate the crisp output. The most common method of defuzzification is the center of gravity method, which is also used in the proposed FRBS.

The result of the defuzzification process is represented as;

$$z^* = \frac{\int \mu_{\tilde{C}}(z)zdz}{\int \mu_{\tilde{C}}(z)dz} \quad (4.3)$$

where $\tilde{C}$ is a fuzzy set with the membership function $\mu_{\tilde{C}}$.

Figure 4.1 shows the calculation steps of the FRBS process for two fuzzy input variables having triangular input membership functions.



Rule 1 If x_1 is A_1 and x_2 is A_2 , then y is C_1
Rule 2 If x_1 is A_1 and x_2 is A_2 , then y is C_2

Figure 4.1 : Sample mamdani (max-min) inference method.

The FRBS is a Mamdani type-1 system that has 23 rules that are used to determine the output. Table 4.1 shows the input membership functions and the a,b, and c values used for each input variable. The fuzzy rules used for target priority determination are shown in Table 4.2. The output variable target priority also has three membership functions, shown in Table 4.3. FRBS input variables used in target priority determination are selected as hostility, range to air defense system, speed, and range to the defended asset. Target priority can also be calculated using the target maneuverability feature. Although the maneuvers of the target can be observed through radar tracks, if the exact type of the target is not known, the total maneuvering capability of the target cannot be fully concluded. In addition, whether a target maneuvers or not, the final aim of the target will be to become closer to the air defense system or the defended assets, which are also included in the target ranges to the closest DA and ADS features. Because of the given reasons, the maneuverability feature of the target is not used in the priority calculation. The input parameters and the rules are selected by a group of expert air defense operators with more than five years of experience in the field, assuming all the targets are fixed-wing, i.e., Fighters. The input variables used in the FRBS are selected as the dominant parameters affecting threat priority for air defense systems. These parameters and rulesets are subject to change for a particular air defense mission or threat set. After the fuzzy inputs are selected, tuning the input and output triangular membership functions and extracting the ruleset from an input dataset using optimization techniques such as genetic is possible [70].

Table 4.1 : Input membership functions.

Input Variable	Membership function	a	b	c
Hostility	Nonhostile	-40000	0.224	0.262
	Unknown	0.185	0.4599	0.774
	Hostile	0.71	0.7398	10000
Range to Air Defense System (m)	Low	-40000	13636.4	28947.4
	Medium	20334.9	30382.8	43301.4
	High	37042.2	46650.7	4e+07
Speed (m/s)	Low	-40000	83.68	171.7
	Medium	117.2	181.2	262.2
	Fast	181	257	4e+07
Range to Defended Asset (m)	Slow	-40000	27512	30861.2
	Medium	23684.2	38995.2	46650.7
	High	38956	51913.9	4e+07

Table 4.2 : Rules used for target priority determination.

Rule	Hostility	Range to Air Defense System	Speed	Range to Defended Asset	Target Priority
#1	Nonhostile	Any	Fast	Any	Medium
#2	Nonhostile	Low	Fast	Any	Low
#3	Nonhostile	Low	Fast	Any	Medium
⋮	⋮	⋮	⋮	⋮	⋮
#11	Unknown	High	Slow	Any	Low
#12	Unknown	High	Medium	Any	Low
#13	Unknown	High	Fast	Any	Medium
⋮	⋮	⋮	⋮	⋮	⋮
#21	Hostile	High	Slow	Low	Low
#22	Hostile	High	Medium	Low	Low
#23	Hostile	High	Fast	Low	Medium

Table 4.3 : Output membership function.

Output Variable	Membership function	a	b	c
Target Priority	Low	-0.4	0	0.4
	Medium	0.1	0.5	0.9
	High	0.6	1	1.6

4.2.2 Maneuver detection

The model probability update stage of the IMM filter is used for maneuver detection in the proposed RRM for networked ADS FCR. The likelihood of each motion model is computed during the model probability update stage after state prediction of mixed state estimates. Innovations $\mathbf{Z}^j(k)$ that are computed in state update and innovation covariance matrix $\tilde{\mathbf{S}}^j(k)$ that is computed in the Kalman gain are used to find the likelihood that is given in Equation 4.4.

$$\Lambda^j(k) = \frac{1}{\sqrt{(|2\pi\tilde{\mathbf{S}}^j(k)|)}} \left[\exp(-0.5)(\mathbf{Z}^j(k))^T(\tilde{\mathbf{S}}^j(k))^{-1}(\mathbf{Z}^j(k)) \right]. \quad (4.4)$$

After the update process of all filter models, the model probabilities are updated accordingly. Updated model probability $\hat{\mu}^j$ for model j is stated as,

$$\hat{\mu}^j(k) = \frac{1}{c} \Lambda^j(k) \bar{\mathbf{c}}^j \quad (4.5)$$

where

$$c = \sum_{i=1}^N \Lambda^i \bar{\mathbf{c}}^i \quad (4.6)$$

is the normalization constant.

IMM tracker with constant velocity and constant turn motion models are used in the fusion center. IMM filter model probabilities $\hat{\mu}^j(k)$ are continuously checked for a change in the target motion model. The model probability of the constant turn motion model being greater than a predefined threshold indicates the start of the maneuver.

4.2.3 Adaptive target tracking and resource management

In the adaptive target tracking part of the algorithm, different tracking rates are assigned according to target priority and maneuver. There are six different tasks associated with the radar network, as shown in Table 5.5. These are the Search task, which has the lowest tracking rate TR_s and the lowest task priority TP_s , Confirm task, which is used to confirm tracks after target detection with tracking rate TR_c and task priority TP_c , TrackNonEngagement task which is used to track low-priority targets with task priority TP_{ne} and tracking rate TR_{ne} , TrackManeuver task which is used to track maneuvering targets with task priority TP_m and tracking rate TR_m and TrackEngageManeuver task used to track both high priority and maneuvering targets with highest task priority TP_{em} and highest tracking rate TR_{em} . The tracking rates are increased according to target priority and target maneuver. Increasing the tracking rate decreases the tracking error and decreases track loss at the expense of an increase in the tracking resources of the radar network.

Table 4.4 : Symbols for FCR tasks, priorities, and tracking rates.

Task	Task Priority	Tracking Rate (Hz)
Search	TP_s	TR_s
Confirm	TP_c	TR_c
TrackNonEngagement	TP_{ne}	TR_{ne}
TrackManeuver	TP_m	TR_m
TrackEngagement	TP_e	TR_e
TrackEngageManeuver	TP_{em}	TR_{em}

Networked FCRs execute the task with the highest task priority at the beginning of each dwell time. Initially, search tasks are executed until a target has been detected. After a target has been detected, a confirmation task is scheduled to initiate the target

tracking. Successful confirmation of the target initiates the scheduling of tracking tasks with higher priorities than the search task. The task priorities of these tracking tasks are assigned according to target priority calculated by FRBS and detection of the maneuver by comparing IMM constant turn model probability with a predefined threshold. After the task with the highest priority is selected for execution, the priorities of the postponed tasks are increased with a certain amount in each dwell. Increasing the priority enables postponed tasks to be executed when they reach the highest value among the other tasks in the scheduler queue.

The algorithm finds the same tracking tasks that are assigned to FCRs in the networked ADS. The range of the track in the overlapping tracking tasks to each radar is calculated. The tracking task is assigned to the closest radar with the lowest number of tracks. Lastly, overlapping redundant tracking tasks for each FCR are eliminated to save radar resources for upcoming search tasks.

Algorithm 1 shows the pseudocode of the proposed method. Firstly, FCR working parameters, including azimuth and elevation search limits and dwell time for each beam, are set according to the requested search volume and detection performance. Secondly, the GNN tracker that will be used in associating detections to tracks is initialized with confirmation and deletion threshold parameters. IMM filter that will be used to track maneuvering targets is initialized with motion models such as Constant Turn and Constant Velocity. Initialization includes assigning initial state covariances for each motion model and transition probabilities used to switch these models. After tracker initialization, FCR TaskList is initialized initially with the search tasks dedicated to the defined search volume. After the radar network starts with the initialized parameters, each measurement from the tasked radars feeds the fusion center to generate the combined air picture. The priority of each target is calculated using FRBS as defined in Section 4.2.2, and the IMM filter tracker output of each track is continuously monitored for maneuver detection.

Algorithm 1 Networked FCR RRM Algorithm utilizing Target Priority and Maneuver Detection

```
1: Initialize FCR Working Parameters
2: Initialize GNN Tracker and IMM Filter
3: Initialize FCR TaskList
4: while RadarNetworkOperates do
5:   Get CurrentTask from the TaskQueue with the highest TaskPriority  $TP_j$  for Each FCR
6:   Increase TaskPriority  $TP_j$  for remaining Tasks
7:   Execute CurrentTask for Each FCR
8:   for Each Measurement  $Y_k$  do
9:     Initialize Target Track or Associate Measurement  $Y_k$  to
       Initiated Network Target Track using GNN
10:  end for
11:  for Each ConfirmedTrack  $T_i$  do
12:    Calculate Target Priority  $T_{p_i}$  using FRBS
13:    Obtain Constant Turn (CT) Model Probability  $\hat{\mu}_i^{CT}$ 
14:    if CurrentTask = Search then
15:      if Detection Exists then
16:        NextTask = Confirm
17:      else
18:        NextTask = Search
19:      end if
20:    else if CurrentTask = Confirm then
21:      NextTask = TrackNonEngagement
22:      TrackingRate  $TR_i = TR_{ne}$ 
23:    else
24:      if  $T_{p_i} > T_{pThreshold}$  and  $\hat{\mu}_i^{CT} > \hat{\mu}_{Threshold}^{CT}$  then
25:        NextTask = TrackEngageManeuver
26:        TrackingRate  $TR_i = TR_{em}$ 
27:      else if  $T_{p_i} > T_{pThreshold}$  then
28:        NextTask = TrackEngagement
29:        TrackingRate  $TR_i = TR_e$ 
30:      else if  $\hat{\mu}_i^{CT} > \hat{\mu}_{Threshold}^{CT}$  then
31:        NextTask = TrackManeuver
32:        TrackingRate  $TR_i = TR_m$ 
33:      else
34:        NextTask = TrackNonEngagement
35:        TrackingRate  $TR_i = TR_{ne}$ 
36:      end if
37:    end if
38:    Schedule NextTask for each FCR
39:  end for
40:  for Each FCR  $R_k$  do
41:    for Each Track  $T_i$  do
42:      Find Overlapping Tracking NextTask for  $T_i$ 
43:      Sort tracks  $T_i$  according to distance to  $R_k$ 
44:      Assign Tracking NextTask to  $R_k$  with the least number of tracks
45:      Eliminate Redundant Search and Tracking NextTask for remaining  $R_k$ 
46:    end for
47:  end for
48: end while
```

4.3 Simulation Results

A sample scenario consisting of two FCR and three DA, as shown in Figure 5.15, has been built to observe the outcome of the proposed networked RRM algorithm. FCR1 is located at (0,0) km and FCR2 is located at (0,20) km. Radars have azimuth coverage of 120 degrees and elevation coverage of 10 degrees. The locations of DAs are (30,20) km, (35,−15) km and (20,−5) km. Targets are prioritized using FRBS with the variables defined in subsection 4.2.1. Different tracking modes with different task priorities and related tracking rates used for each radar mode are shown in Table 4.5. The task priorities in the simulation scenario emphasize tracking tasks over search tasks, which results in more radar resources being allocated to target tracking rather than surveillance, especially in saturation conditions.

All targets that are used in the simulation scenario are hostile. Simulation results are obtained for 10, 15, and 22 targets labeled P1 through P22. The scenario is simulated with different modes of operation while new target trajectories are added to previous ones to better understand the algorithm's outcome in an increased threat environment. IMM filter is used for target tracking as described in 4.2.2. The IMM Filter uses two target models: constant velocity and constant turn. GNN tracker is initialized with the confirmation and deletion threshold parameters as follows: A confirmation for the track is done if it receives two detections out of three updates. A track deletion is performed if the confirmed track is not assigned to any detection 5 times in the last 5 tracker updates. Munkres [5] algorithm which minimizes the total cost of assignments to obtain an optimal solution is used in the GNN assignment process. Matlab R2023a with sensor fusion and tracking toolbox is used to code and simulate the scenario.

Table 4.5 : FCR tasks, priorities, and tracking rates used in simulation.

Task	Task Priority	Tracking Rate (Hz)
Search	800	0
Confirm	3000	20
TrackNonEngagement	1500	0.6
TrackManeuver	2000	1
TrackEngagement	2500	2
TrackEngageManeuver	3500	4

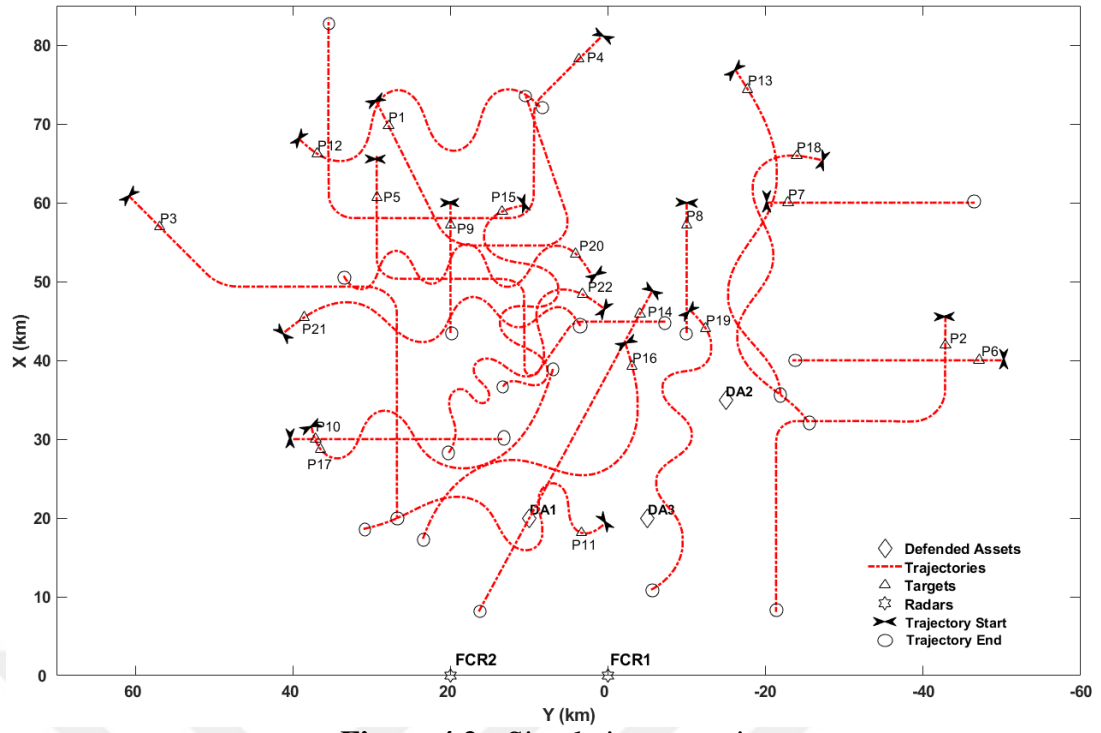


Figure 4.2 : Simulation scenario.

Two different working modes for the networked radars are investigated for comparison: uncooperative and cooperative. In the first case, two ADS FCRs are operated independently, i.e., uncooperative, working with the constant update rates defined in Table 4.5, detecting and tracking the targets in the scenario and feeding those detections to a centralized fusion center. In the second mode, the radars work cooperatively according to the algorithm defined in Algorithm 1. The threshold value for the target priority $T_{pThreshold}$ is set to 0.85, and the model probability change threshold $\hat{\mu}_{Threshold}^{CT}$ is selected as 0.7. Normalized resource utilization and frame time vs. time graphs will be given for each mode. Normalized resource utilization graphs show mainly the normalized distribution of search and tracking tasks within a two-second period. The x-axis in the graph shows the time step, and the y-axis shows the fraction of the time spent on each FCR task. The frame time is the time for each radar to complete its search cycle defined in its surveillance volume. Increasing frame time shows the degradation in the search capability of the radar.

The normalized search and track allocation while the scenario is simulated with a different number of targets for uncooperative working mode is shown in Figure 4.3 and Figure 4.4 respectively. The search and track allocation graphs for each target scenario almost add up to unity. This is because the radar tasks consist of confirmation,

search, and tracking tasks. The radar is assigned with confirmation tasks when a detection occurs, and after confirmation with the subsequent detection, tracking tasks are formed. Confirmation tasks resource allocation is minimal compared to search and tracking tasks in the simulation and occurs only before the beginning or during loss and reinitiation of the track.

The radars operate independently with the same tracking rates, which leads to the same amount of task allocation. As can be seen from the graphs, increasing the number of targets increases search allocation, which finally leads to saturation in the 22-target scenario. With the increase in search allocation, the track capacity decreases. For the 22 target scenario, track capacities of the radars are fully allocated through the end of the simulation.

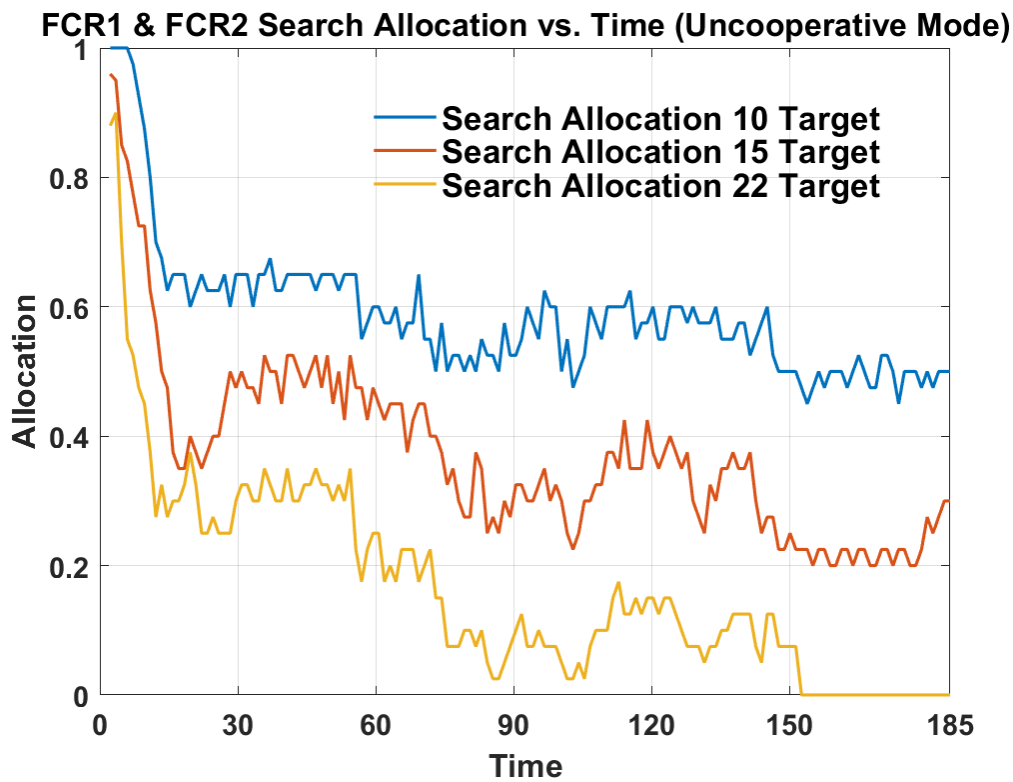


Figure 4.3 : FCR1 and FCR2 search allocation vs.time (uncooperative mode).

In the second case, FCRs are operated in a networked configuration cooperating as defined in Algorithm 1. For each target, after the tracking starts with the detection of any radar, the tracking task is handed over to the radar with the closest distance instead of all radars tracking the target as in uncooperative mode. Search and track resource utilization for cooperated mode operation is shown in Figure 4.5 and Figure 4.6 for FCR1. The cooperation between networked radars defined in Algorithm 1

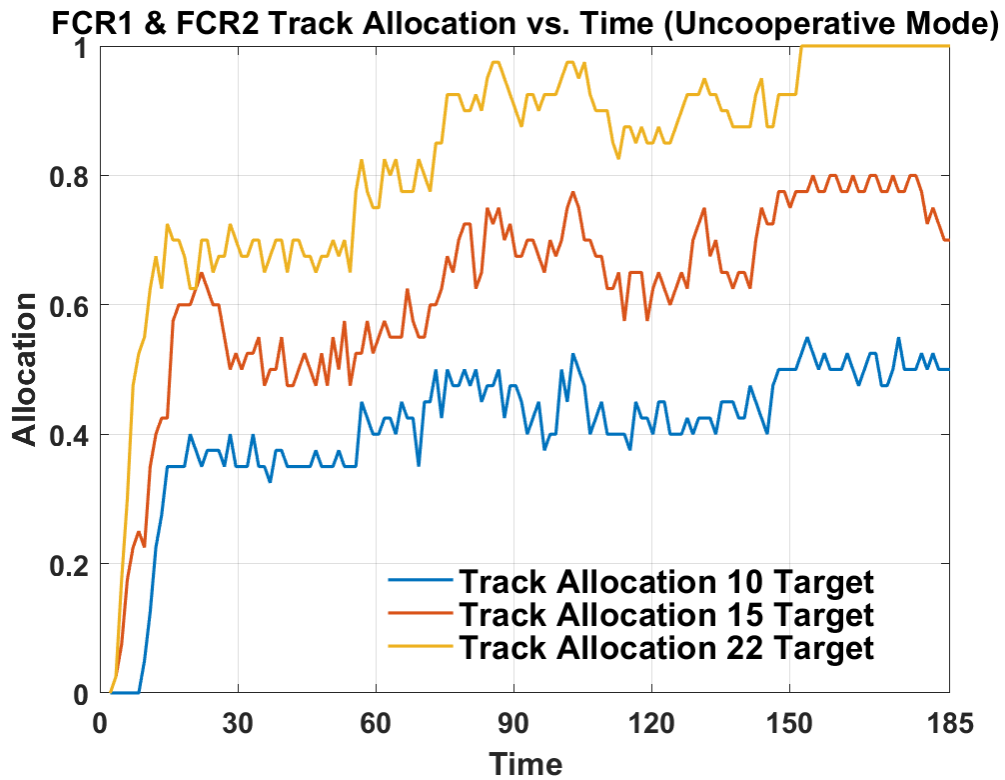


Figure 4.4 : FCR1 and FCR2 track allocation vs.time (uncooperative mode).

results in increased search capacity and decreased tracking load due to sharing of the tracking tasks and eliminating overlapping tasks compared to uncooperative mode task allocation graphs shown in Figure 4.3 and Figure 4.4.

Search and track allocation for the second fire control radar FCR2 are shown in Figure 4.7 and Figure 4.8. Due to the targets' trajectory and distance of the targets to the radars, in cooperative mode, different search and track allocation performances are obtained for FCR1 and FCR2. As seen from the FCR1 and FCR2 radar task allocation graphs, the cooperative mode increased the search capacity. Also, it decreased the track allocation of both radars compared to the uncooperative operation mode.

The search capability of the ADS multifunction FCR is essential for system defense effectiveness. The targets shall be detected, and the tracks shall be initiated as quickly as possible to increase the engagement window for the threatening targets. The frame time is a crucial parameter of a radar having search capability. The frame time is the amount of time that passes when a radar searches a predefined volume. A lower frame time is better for quickly scanning the area of interest and detecting new targets that appear in the scenario. Frame time vs. time graphs for uncooperative and cooperative operating modes of networked radars are shown in Figures 4.9 and 4.10. The frame

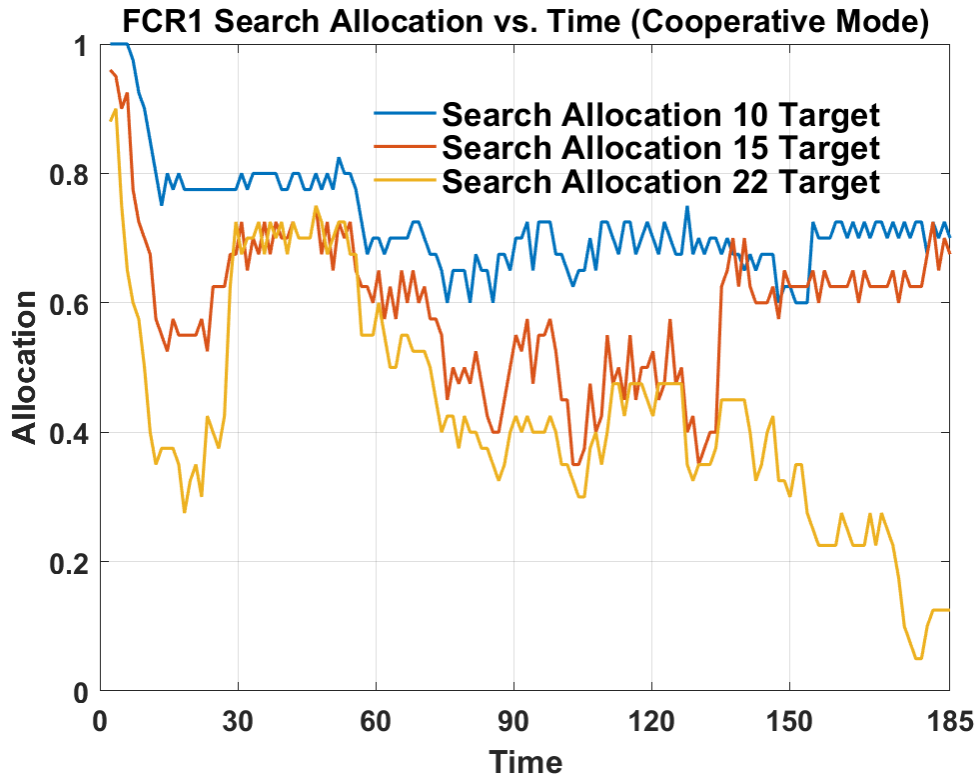


Figure 4.5 : FCR1 search allocation vs.time (cooperative mode).

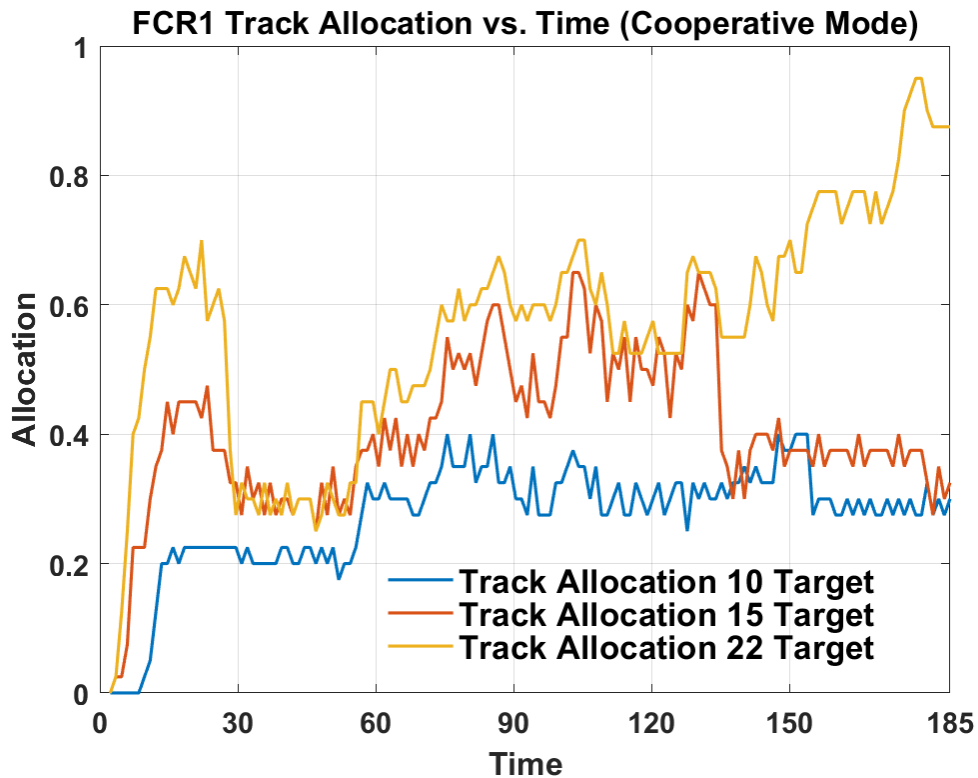


Figure 4.6 : FCR1 track allocation vs.time (cooperative mode).

time for the uncooperative mode increases above 55 seconds for the 22-target case for both radars because the radars are fully allocated with tracking tasks. With cooperative

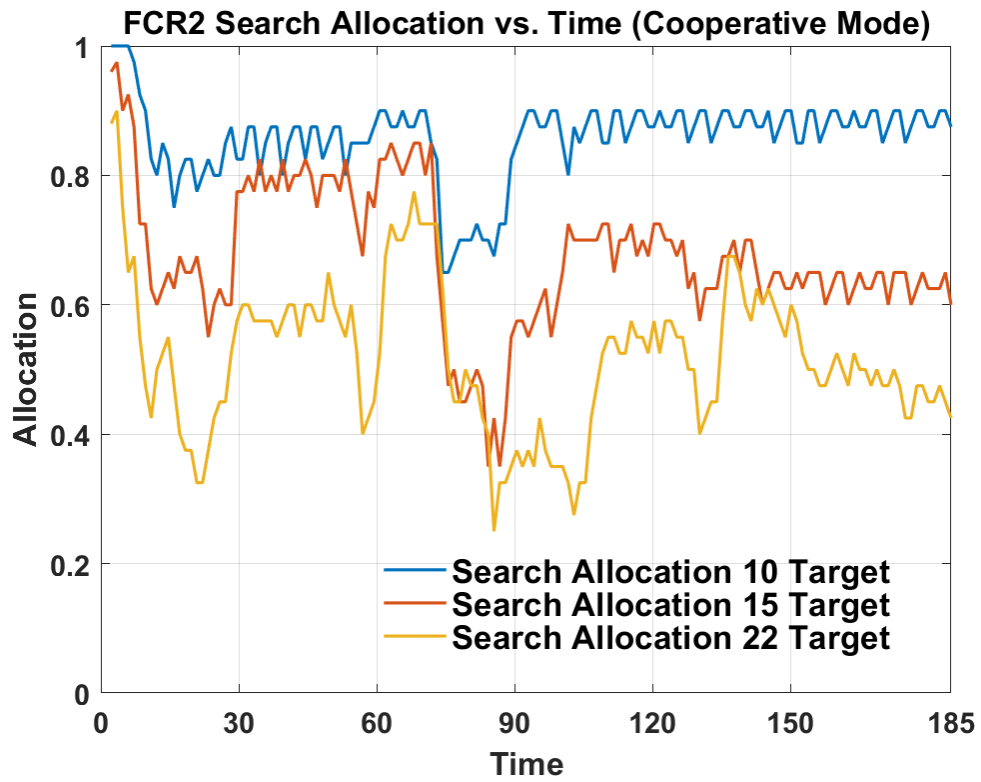


Figure 4.7 : FCR2 search allocation vs.time (cooperative mode).

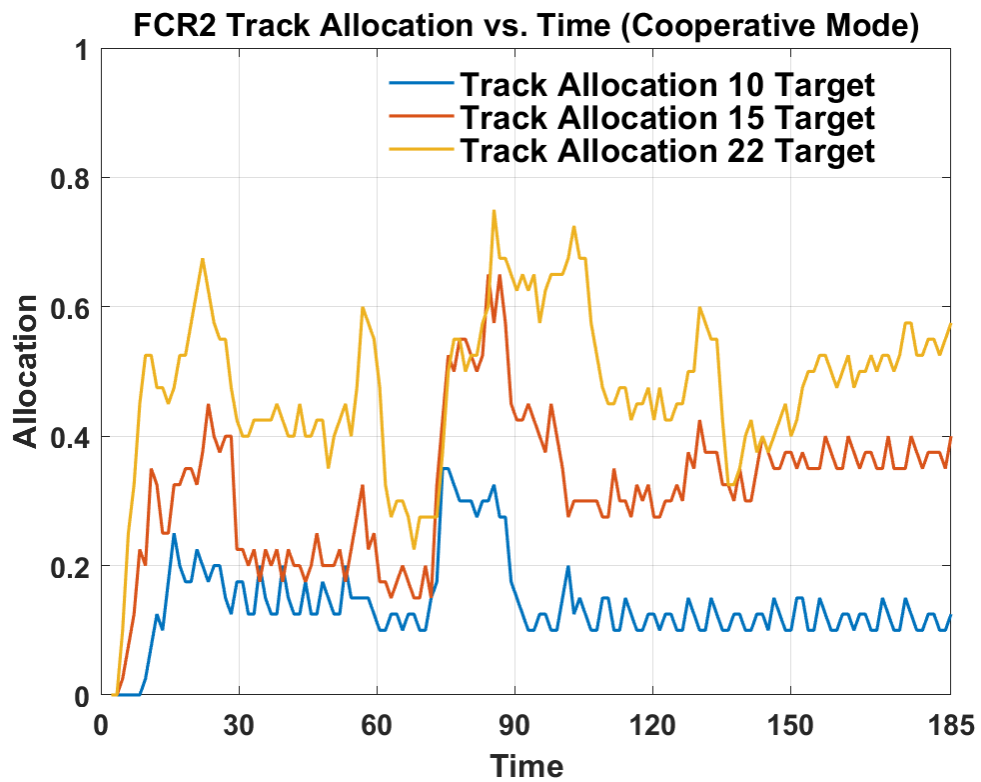


Figure 4.8 : FCR2 track allocation vs.time (cooperative mode).

operation mode utilizing the proposed algorithm, the maximum frame time of both

radars decreased to around 30 seconds for FCR1 and less than 30 seconds for FCR2, which is around %45 improvement.

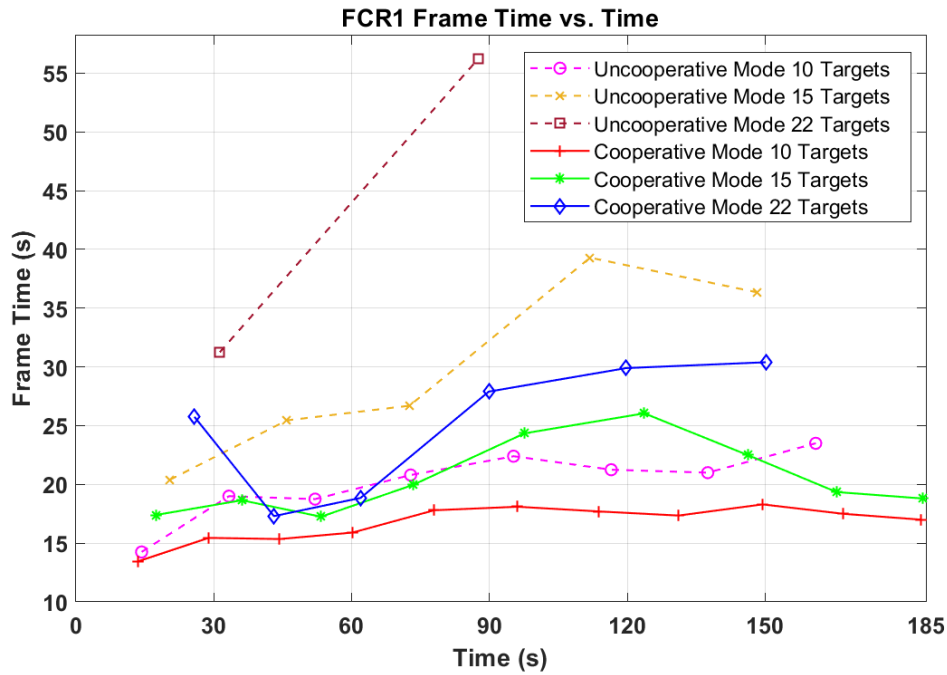


Figure 4.9 : FCR1 frame time vs. time (uncooperative and cooperative modes).

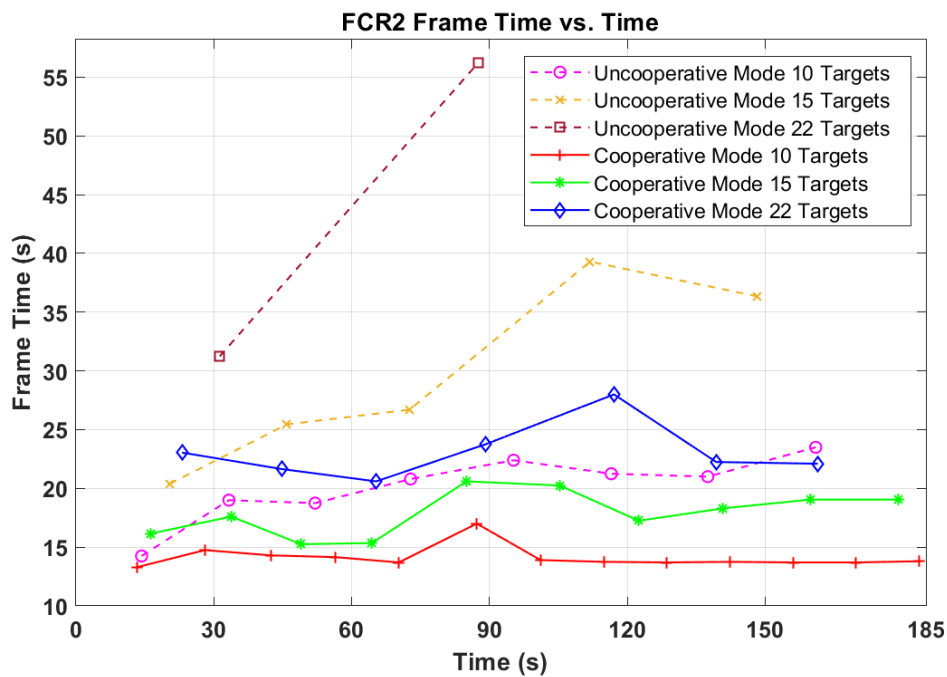


Figure 4.10 : FCR2 Frame time vs. time (uncooperative and cooperative modes).

Track initiation time, vital for air defense systems, is the elapsed time between the target appearing in the surveillance volume of the radars and the formation of the target track. The track initiation time for the 22-target case is shown in Table 4.6. As seen

from the table, there is an improvement in the track initiation time for most of the targets, and the average improvement is around %13 for all the tracks, excluding Track 20. No track is formed since the uncooperative mode search capacity is fully loaded for the 22-target case. On the other hand, the track is initiated at 4.15 seconds in the cooperative operation mode. Decreased track initiation time in the cooperated mode will eventually increase the engagement timeline for the targets that have higher priority.

Table 4.6 : Track initiation time for uncooperative and cooperative modes.

Uncooperated Mode		Cooperated Mode	
Target#	Track Initiation Time (s)	Target#	Track Initiation Time (s)
1	22	1	17.35
2	12.65	2	11.15
3	27.8	3	20.7
4	2.6	4	2.6
5	23.75	5	17.8
6	12.4	6	10.7
7	5.7	7	5.2
8	4.9	8	4.8
9	21.55	9	16.45
10	26.6	10	20.2
11	2.4	11	2.4
12	23.85	12	18.35
13	5	13	4.8
14	4.75	14	4.6
15	20.8	15	15.85
16	4.85	16	4.7
17	26.55	17	20.3
18	5.9	18	5.25
19	5.1	19	4.9
20	No Track	20	4.15
21	25.1	21	19.2
22	2.5	22	2.5

The proposed algorithm adapts tracking rates according to target priority and maneuver with the rates defined in Table 4.5. The commanded and achieved tracking rates indicate how well the radar network performs adapted tracking. Examples from the 22-target case will be explored respectively to represent the change of the tracking rate of the FCR network with the change of target priority and maneuver. Figure 4.11

shows the target priority vs. time graphs and commanded tracking rate vs. achieved tracking rate for Target 12. As seen from the graph, Target 12 is far from the FCRs and DAs. Hence, target priority is low according to the rules of FRBS. The target is tracked with the lowest tracking rate since the target priority doesn't pass the priority threshold. However, the target maneuvers during its flight; hence, the tracking rate is increased to 1 Hz during detected maneuvers that pass the maneuver threshold filter.

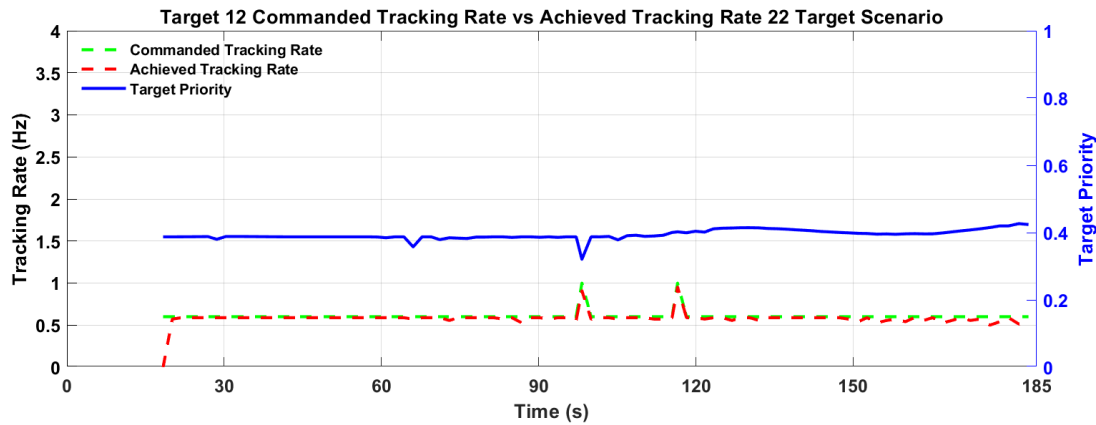


Figure 4.11 : Target priority vs. time and tracking rate vs. time graph for target 12.

Figure 4.12 shows target priority and tracking rates for Target 22. The figure also shows the commanded tracking rate and the achieved tracking rate of the radar network. Commanded tracking rate is the assigned tracking rate of the target depending on the target priority and maneuver. However, due to competing tasks, the commanded tracking rate can not be achieved when the priority of postponed tasks reaches the highest value. The achieved tracking rate shows the final target tracking rate after radar tasks in the network are scheduled. Initially, target priority is above the threshold, and high-priority tracking is performed. While the target is heading outbound from the FCRs and DAs, target priority decreases, hence the target tracking rates decrease. It can be seen from the graph that the tracking rate is increased during detected maneuvers that pass the maneuver threshold filter.

Figure 4.13 shows the target priority of Target 13 with the commanded and achieved target tracking rates. After the target priority has increased above the threshold value of 0.85, around 80 seconds, FCRs are commanded to track the target with the engagement tracking rate of 2 Hz. The commanded tracking rate has been achieved for more than 20 seconds. Nevertheless, due to an increase in the tracking load of the radar network, the achieved tracking rate decreased to around 1.6 Hz. The networked cooperative FCR

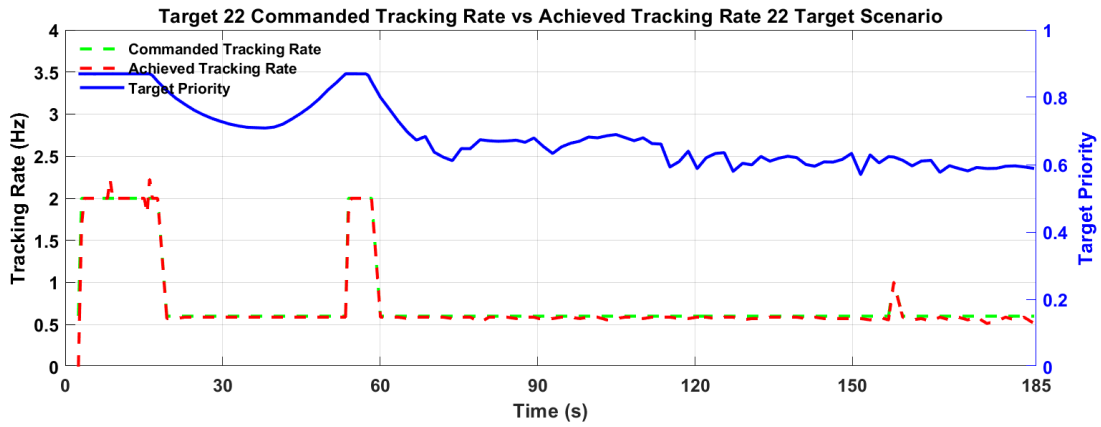


Figure 4.12 : Target priority vs. time and tracking rate vs. time graph for target 22.

responded to the target maneuver by increasing the commanded tracking rate to 4 Hz around 130 s. The reason why the radar network has achieved the commanded tracking rate can be described as follows. The task priority for high-priority maneuvering targets is the highest among other tasks. The radar network can achieve the required tracking by postponing the other radar tasks. After the maneuver has ended, the radar network changes the tracking rate to 2 Hz for Target 13. As the resources of the radar network are available, the target is tracked at the requested tracking rate.

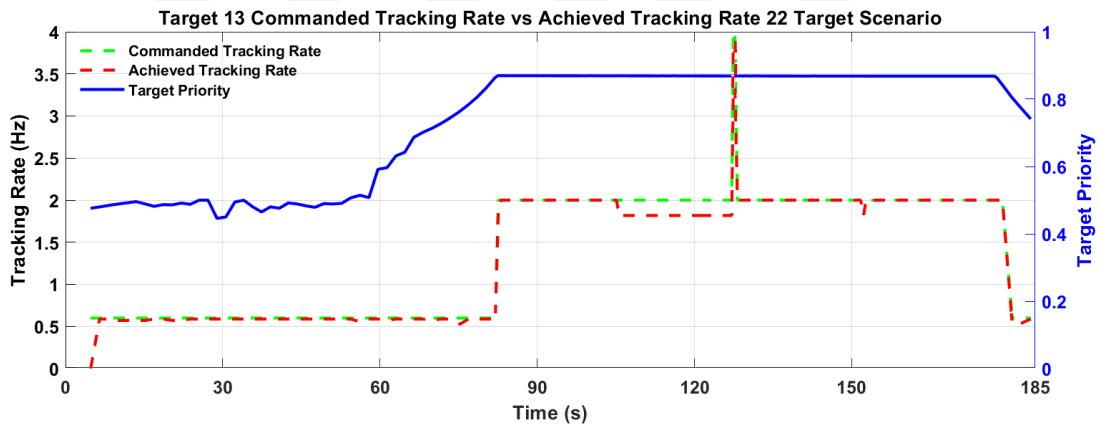


Figure 4.13 : Target priority vs. time and tracking rate vs. time graph for target 13.

Another important metric for system performance is tracking quality. This metric is important because, after the engagement decision and execution phase, targets are engaged using fire control quality tracks formed in the network. This tracking quality shall be above the tracking quality requirement of the ADS interceptors. Figure 4.14 shows RMSE tracking error vs. time for the non-adaptive cooperative tracking and adaptive rate cooperative tracking network for the 22-target case. Although tracking quality for the non-adaptive cooperative tracking surpasses adaptive cooperative tracking at the beginning of the simulation, tracking quality has decreased

as more targets are detected and tracked by the networked FCRs. The leading cause for this degradation is the saturation of the FCRs working in the non-adaptive configuration. The comparison shows that adaptive cooperative RRM working as defined in Algorithm 1 performs better than the non-adaptive cooperative RRM in a high number of maneuvering high-priority target environments.

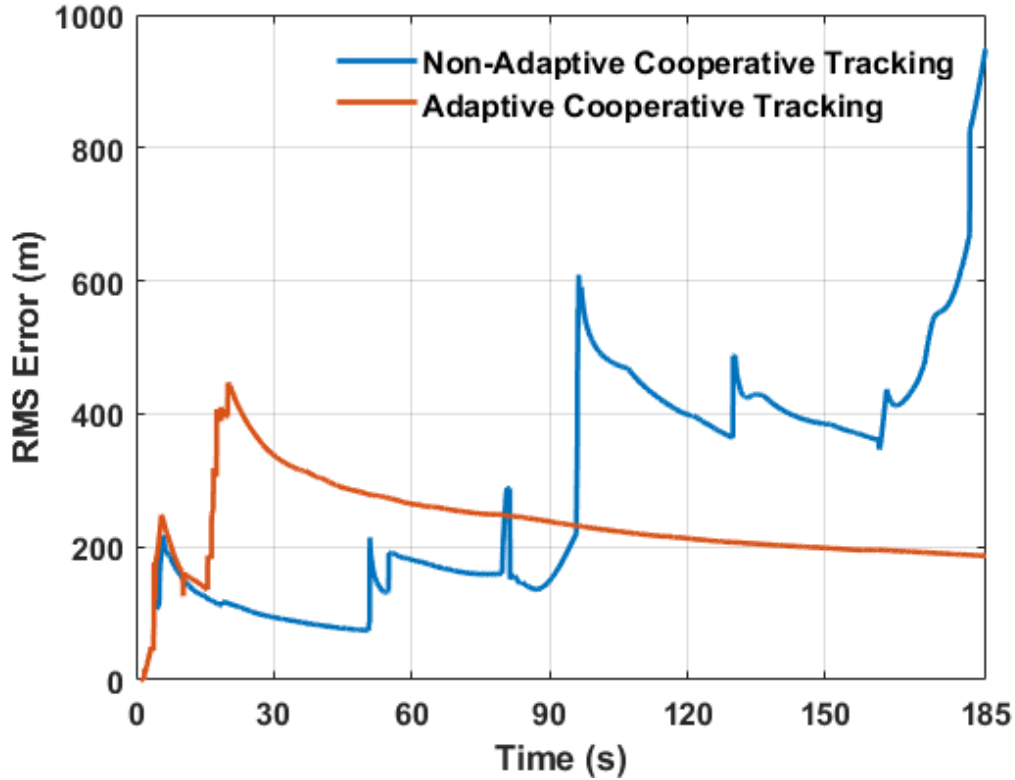


Figure 4.14 : RMS track error for non-adaptive and adaptive cooperative target tracking.

4.4 Summary and Discussion

In this chapter, an algorithm to manage the resources for cooperative FCR in networked ADS has been proposed. In addition to previous studies that utilize only target priority or target maneuver for resource allocation, the proposed algorithm utilizes adaptive target tracking, which considers both the priority of targets calculated using a fuzzy rule-based system and the maneuver of those targets detected using IMM filter model probabilities. As the targets are tracked by the networked radars, overlapping tasks for networked FCRs are removed to increase the search capability and decrease the tracking capability while keeping the tracking quality needed for interceptor engagement. The benefits of the proposed algorithm are observed by

simulating a sample scenario consisting of two FCRs and three DAs with an increasing number of targets. Simulation results show that when the number of targets increases leading to saturation, the cooperative mode of operation decreases the utilization of tracking resources for both FCRs, allowing more resources for the search functionality compared to the uncooperative operation of both FCRs. Increased search capability resulting from the cooperative working mode eventually decreases the frame time of FCRs and reduces track initiation times. As a final observation, the adaptive target tracking mode of these cooperative FCRs is compared with a non-adaptive target tracking rate for cooperative FCRs. RMSE for high-priority targets has been improved for the high number of threats, as the tracking filter settles in the adaptive cooperative tracking case. Simulation results showed that the proposed method utilizing target priority and target maneuver detection will increase the defense effectiveness of the networked ADS by decreasing the tracking load, allowing more targets to be tracked, and increasing the search capability, which will decrease the track initiation time of tracks. It is also shown that the proposed algorithm also decreased RMS tracking error, especially for a high number of maneuvering high-priority targets.



5. RESOURCE MANAGEMENT OF NETWORKED AIR DEFENSE RADARS USING OPTIMIZATION TECHNIQUES

Radar resource management of networked air defense system radars is studied in this section. Algorithm utilizing surrogate optimization have been proposed which aim to select optimum number of radars to satisfy changing tracking quality requirements according to target priority. As a second case study, the algorithm is extended under tracking and transmit power constraints. The advantages of these algorithms are presented with simulation studies consisting of several networked radars, defended assets and targets.

5.1 RRM of Networked Air Defense Radars Using Optimization Techniques

The development of radar resource management algorithms for networked radars requires modeling of the system and the target states. Generally, two-dimensional state space representation is used for the target states. A performance metric is optimized under certain constraints.

5.1.1 System model

We assume that the FCRs of the ADS network are identical and working in perfect synchronization. To form the system model, we need a target state model for each target and a measurement model for our radars, which will be used to calculate the detection parameters from those targets.

5.1.1.1 Target state model

The state vector of the q th target at the time instant k is given as $\mathbf{X}_k^q = [x_k^q, \dot{x}_k^q, y_k^q, \dot{y}_k^q]^T$. We are considering a two-dimensional state space, and the vector elements represented here are x and y coordinates, and the velocity of the target is represented by $\dot{x}$ and $\dot{y}$ along these coordinates. Since we are considering long-range radars, the targets are assumed to have a constant velocity (CV) motion model represented by

$$\mathbf{X}_k^q = \mathbf{F}^q \mathbf{X}_{k-1}^q + \mathbf{W}_{k-1}^q \quad (5.1)$$

$\mathbf{F}^q$ represents the transition matrix for q th target at k th time frame, and the target motion has an additive Gaussian noise $\mathbf{W}_{k-1}^q$ with a known covariance $\mathbf{Q}_{k-1}^q$, which are given by

$$\mathbf{F}^q = \begin{bmatrix} 1 & \Delta T_k^q \\ 0 & 1 \end{bmatrix} \otimes \mathbf{I}_2 \quad (5.2)$$

and

$$\mathbf{Q}_{k-1}^q = \begin{bmatrix} \frac{(\Delta T_k^q)^3}{3} & \frac{(\Delta T_k^q)^2}{2} \\ \frac{(\Delta T_k^q)^2}{2} & \Delta T_k^q \end{bmatrix} \otimes \mathbf{I}_2, \quad (5.3)$$

where $\otimes$ is the Kronecker operator and $\mathbf{I}_2$ is the order 2 identity matrix.

5.1.1.2 Measurement model

Measurement for radar node i at the time instant k for target q has the form

$$\mathbf{z}_{i,k}^q = \mathbf{h}_i(\mathbf{X}_k^q) + \mathbf{v}_{i,k}^q. \quad (5.4)$$

In equation (5.4), the measurement function is $\mathbf{h}_i(\mathbf{X}_k^q)$, measured parameters of the target are range and bearing, and $\mathbf{v}_{i,k}^q$ is the noise measurement vector which is assumed to be white Gaussian with variances $\sigma_{R_{i,q,k}}^2$ for range measurement and $\sigma_{\theta_{i,q,k}}^2$ for azimuth measurement

$$\mathbf{h}_i(\mathbf{X}_k^q) = \begin{bmatrix} R_{i,q,k} \\ \theta_{i,q,k} \end{bmatrix} = \begin{bmatrix} \sqrt{(x_k^q - x_i)^2 + (y_k^q - y_i)^2} \\ \arctan \frac{(y_k^q - y_i)}{(x_k^q - x_i)} \end{bmatrix}. \quad (5.5)$$

5.1.2 Fusion center

The Fusion Center in the networked ADS system performs a centralized fusion of target detection measurements from the multifunction fire control radars. In the centralized fusion architecture, all the measurements from the radars are sent to a fusion center through reliable communication links in which track association is performed and system tracks are generated. All ADS can have their own fusion capability when they are working in autonomous working mode, fusing sensor data from their internal and externally connected sensors. When ADS are working in networked mode, one of them can take the responsibility of sensor fusion to form centralized system tracks. These centralized tracks are then distributed to other defense systems in the network. Although there is another possible architecture named decentralized architecture in which all systems exchange their sensor data to all other nodes and generate the air picture independent from each other, centralized

fusion architecture needs less communication bandwidth and computation resources at the expense of a single point of failure drawback that emanates from single system performing the fusion [115]. Hybrid architectures combining the advantages of both centralized and decentralized architecture is also possible [5]. Extended Kalman Filter (EKF) is used in the track filter of the Central Fusion block. EKF has been one of the most widely used methods for tracking and estimation based on its apparent simplicity, optimality, tractability, and robustness, which is an extension of the Kalman filter (KF). In the EKF, KF is applied to non-linear process and measurement models by linearizing the models. The update equation of the EKF is of the same form as the linear KF:

$$\hat{\mathbf{x}}(k|k) = \hat{\mathbf{x}}(k|k-1) + K(k) \{ \mathbf{y}(k) - h[\hat{\mathbf{x}}(k|k-1)] \} \quad (5.6)$$

Where $h[\hat{\mathbf{x}}(k-1|k)]$ is generally a nonlinear measurement function, K is the gain. The gain computation is similar to linear KF:

$$K(k) = P(k|k-1) H_x'(k) [H_x(k) P(k|k-1) H_x'(k) + R(k)]^{-1} \quad (5.7)$$

H_x is the linearized measurement matrix defined by

$$H_x(k) = \left. \frac{\partial h}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}(k-1|k)} \quad (5.8)$$

and P is the state estimation covariance matrix, and R is the measurement noise covariance matrix. H_x has dimensions $d \times m$ where d is the dimension of the estimated state vector and m is the dimension of the measurement. For a two-dimensional filter with a state vector of size 4, which is given as:

$$\mathbf{x} = \begin{bmatrix} x \\ v_x \\ y \\ v_y \end{bmatrix} \quad (5.9)$$

and a radar measurement of range ($\mathcal{R}$) and azimuth angle (η) ($m = 2$)

$$\mathbf{y} = h(\mathbf{x}) = \begin{bmatrix} \mathcal{R} \\ \eta \end{bmatrix} = \begin{bmatrix} (x^2 + y^2)^{1/2} \\ \tan^{-1}(y/x) \end{bmatrix}. \quad (5.10)$$

The measurement function is defined as;

$$H_x = \begin{bmatrix} \frac{\partial \mathcal{R}}{\partial x} & \frac{\partial \mathcal{R}}{\partial v_x} & \frac{\partial \mathcal{R}}{\partial y} & \frac{\partial \mathcal{R}}{\partial v_y} \\ \frac{\partial \eta}{\partial x} & \frac{\partial \eta}{\partial v_x} & \frac{\partial \eta}{\partial y} & \frac{\partial \eta}{\partial v_y} \end{bmatrix}_{\mathbf{x}=\hat{\mathbf{x}}} = \begin{bmatrix} \frac{\hat{x}}{\hat{R}} & 0 & \frac{\hat{y}}{\hat{R}} & 0 \\ \frac{\hat{y}}{\hat{R}^2} & 0 & \frac{\hat{x}}{\hat{R}^2} & 0 \end{bmatrix} \quad (5.11)$$

where $\hat{R} = \sqrt{(\hat{x}^2 + \hat{y}^2)}$.

5.1.3 Performance metric: BFIM

In the Bayesian estimation problem, the Bayesian Cramér-Rao Lower Bound C_k provides a lower bound on the MSE matrix Σ_k in guessing the random parameter vector x_k .

The BCRLB inequality shows the expectation that is taken with respect to the target state and measurement state, which is the Mean Square Error (MSE) of any state vector cannot go below a lower bound that is given by,

$$\mathbb{E}_{\mathbf{X}_k^q, \mathbf{z}_k^q} \{ (\hat{\mathbf{X}}_k^q(\mathbf{z}_k^q) - \mathbf{X}_k^q)(\hat{\mathbf{X}}_k^q(\mathbf{z}_k^q) - \mathbf{X}_k^q)^T \} \geq \mathbf{J}^{-1}(\mathbf{X}_k^q) \quad (5.12)$$

where $\mathbf{J}^{-1}(\mathbf{X}_k^q)$ represents the BFIM for the q th target. $\mathbb{E}\{\bullet\}$ represents the mathematical expectation and $(\mathbf{z}_k^q)$ represents the observation vector.

BFIM can be written as:

$$\mathbf{J}(\mathbf{X}_k^q) = -\mathbb{E}_{\mathbf{X}_k^q, \mathbf{z}_k^q} \left\{ \Delta_{\mathbf{X}_k^q}^{\mathbf{X}_k^q} \log p(\mathbf{z}_k^q, \mathbf{X}_k^q) \right\} \quad (5.13)$$

where $\Delta_{\mathbf{X}_k^q}^{\mathbf{X}_k^q} = \nabla_{\mathbf{X}_k^q} \nabla_{\mathbf{X}_k^q}^T$. $\nabla_{\mathbf{X}_k^q}$ operator denotes the first order partial derivative vector.

Equation (5.13) can be represented as

$$\mathbf{J}(\mathbf{X}_k^q) = -\mathbb{E}_{\mathbf{X}_k^q, \mathbf{z}_k^q} \left\{ \Delta_{\mathbf{X}_k^q}^{\mathbf{X}_k^q} \log p(\mathbf{X}_k^q) p(\mathbf{z}_k^q | \mathbf{X}_k^q) \right\}. \quad (5.14)$$

Using the fact that the logarithm of the multiplication of two functions is the sum of the logarithm of those functions, the BFIM can be formulated as [116]

$$\mathbf{J}(\mathbf{X}_k^q) = \mathbf{J}_P(\mathbf{X}_k^q) + \mathbf{J}_z(\mathbf{X}_k^q) \quad (5.15)$$

where $\mathbf{J}_P(\mathbf{X}_k^q)$ is the prior information and $\mathbf{J}_z(\mathbf{X}_k^q)$ is the information gained by measurement:

$$\begin{aligned} \mathbf{J}_P(\mathbf{X}_k^q) &= \mathbb{E}_{\mathbf{X}_k^q} \left\{ -\Delta_{\mathbf{X}_k^q}^{\mathbf{X}_k^q} \log p(\mathbf{X}_k^q) \right\} \\ \mathbf{J}_z(\mathbf{X}_k^q) &= \mathbb{E}_{\mathbf{X}_k^q, \mathbf{z}_k^q} \left\{ -\Delta_{\mathbf{X}_k^q}^{\mathbf{X}_k^q} \log p(\mathbf{z}_k^q | \mathbf{X}_k^q) \right\}. \end{aligned} \quad (5.16)$$

In the ADS, we have different radars independently observing the target q at time index k ; the BFIM is the sum of priori information plus the sum of information gained by observation of each radar. Using this fact, BFIM can be formulated as:

$$\mathbf{J}(\mathbf{X}_k^q) = \mathbf{J}_P(\mathbf{X}_k^q) + \sum_{i=1}^N u_{i,k}^q \mathbf{J}_D^{(i)}(\mathbf{X}_k^q) \quad (5.17)$$

where $\mathbf{J}_D^{(i)}(\mathbf{X}_k^q)$ is the corresponding component of FIM coming from the i th radar observation. $u_{i,k}^q$ is the binary variable that represents whether there is a measurement from the corresponding radar or not.

BFIM can be approximated as

$$\mathbf{J}(\mathbf{X}_k^q) = [\mathbf{Q}^q + [\mathbf{F}\mathbf{J}^{-1}(\mathbf{X}_{k-1}^q)\mathbf{F}^T]^{-1} + \sum_{i=1}^N u_{i,k}^q \{(\mathbf{H}_{i,k}^q)^T (\mathbf{G}_{i,k}^q)^{-1} (\mathbf{H}_{i,k}^q)\}] \Big|_{(\mathbf{X}_{k|k-1}^q)} \quad (5.18)$$

for small process noise assumption [117] where $\mathbf{H}_{i,k}^q$ is the Jacobi matrix of $h_i(\mathbf{X}_k^q)$. The predicted BCRLB of target q can be expressed as the inverse of the predicted BFIM such that

$$\mathbf{C}_{k|k-1}^q = [\mathbf{J}(\mathbf{X}_{k|k-1})]^{-1} \quad (5.19)$$

where diagonal elements of $\mathbf{C}_{k|k-1}^q$ stand for the CRLBs on the variances of target estimates. Consequently, the lower bound on the metric representing the tracking performance for target q is defined as

$$\mathbb{F}_{k|k-1}^q \triangleq \sqrt{C_{k|k-1}^q(1,1) + C_{k|k-1}^q(3,3)}. \quad (5.20)$$

In (5.20), $C_{k|k-1}^q(1,1)$ and $C_{k|k-1}^q(3,3)$ represent the diagonal elements of $\mathbf{C}_{k|k-1}^q$. The worst-case tracking BCRLB is a representation of the target with maximum BCRLB, which is the trace of the equation (5.19).

5.2 Case Study-1: Target Priority Based Networked Radar Resource Optimization Strategy

To solve the problem of assigning the tracking radars in an ADS, the proposed method utilizes FRBS-based threat priority calculation to adaptively select the tracking quality requirement for each target. A surrogate-based optimization algorithm is then used to determine the minimum number of tracking radars to minimize the cost function formed by the tracking quality metric and BCRLB.

5.2.1 Target priority determination

Target prioritization based on fuzzy logic has also been applied to radar resource management on networked radars [30]. Considering the research done, the use of fuzzy logic for prioritization for targets in an ADS network consisting of phased array radar fire control radars seems viable. A decision tree for target priority assessment

has to be created to form the fuzzy input data set. Target priority determination in previous studies included weapon system capabilities, hostility, degree of threat, and position to the radar system [118, 119]. However, since ADS are deployed to protect defended assets (DA), additional important variables that have to be considered in the decision tree are the CPA d_{CPA} and the time to reach this CPA t_{CPA} . Those variables and the distance to the closest defended asset are also included in the input data set in our FRBS. ADS and their fire control radars are also considered as DAs in the view of self-defense. The distance to those radars is also considered when calculating the threat priority. Figure 5.1 shows the decision tree for the fuzzy variables used for target priority assessment in this chapter.

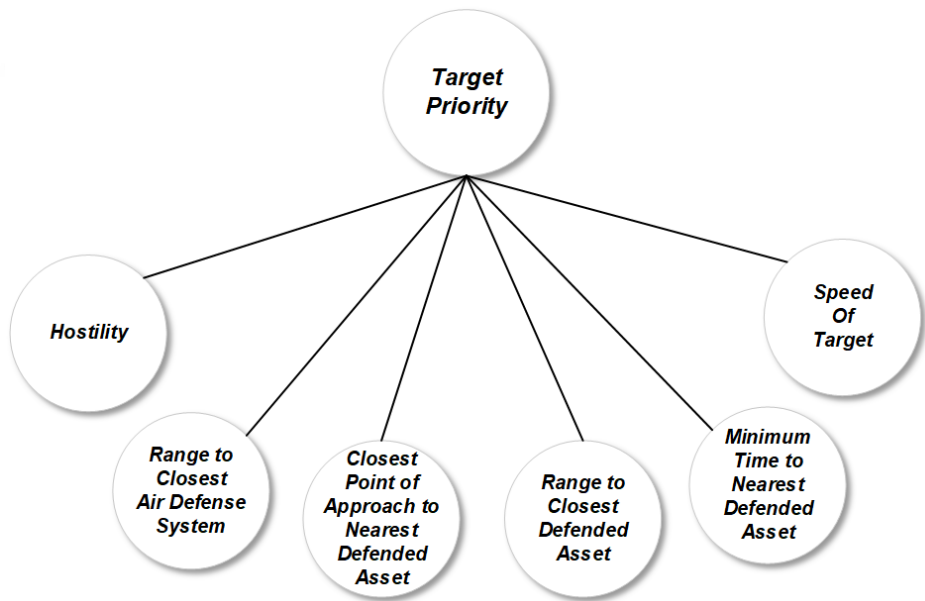


Figure 5.1 : Target priority assignment decision tree variables.

Considering $\mathbf{X}_k^q = [x_T, \dot{x}_T, y_T, \dot{y}_T]^T$ to be the state of the target, since DA is stationary, its velocity components are zero in x and y coordinates, the state of the DA can be expressed as $\mathbf{X}_{DA} = [x_{DA}, 0, y_{DA}, 0]^T$. The calculation of t_{CPA} and d_{CPA} for a target to a DA is as follows:

$$t_{CPA} = -\frac{(p_x v_x + p_y v_y)}{\sqrt{v_x^2 + v_y^2}} \quad (5.21)$$

$$d_{CPA} = \sqrt{(p_x + t_{CPA} v_x)^2 + (p_y + t_{CPA} v_y)^2}.$$

where

$$\mathbf{p} = [p_x, p_y]^T = [x_T, y_T]^T - [x_{DA}, y_{DA}]^T \quad (5.22)$$

and

$$\mathbf{v} = [v_x, v_y]^T = [v_T, v_T]^T. \quad (5.23)$$

The set of fuzzy values that are used for each variable are shown in Table 5.1. As seen from the table, there are six variables, each with three different fuzzy values.

Table 5.1 : Fuzzy rule-based system (FRBS) variables.

Parameter	Value
Hostile	Friend, Unknown, Hostile
Range to ADS	Low, Medium, High
Time to CPA	Low, Medium, High
Distance to CPA	Low, Medium, High
Range to Closest DA	Low, Medium, High
Speed	Slow, Medium, Fast

After deciding the input variables, a membership function (MF) is set for each input. An MF is a curve that maps each point in the input space into a membership value between 0 and 1. MFs can be constructed from triangular, trapezoidal, gaussian, sigmoidal, or bell-shaped functions [120]. It is also possible to build user-defined MFs. Selection of the MF is an active field of research in fuzzy logic systems and mainly depends on the nature of the problem. Figure 5.2 shows the selected MFs for the Hostile and Speed inputs. The hostility is an output of the threat identification process in an ADS. In addition to positive identification methods such as Identification Friend or Foe (IFF), passive control measures such as control of air tasking order and restricted air space control measures are also used to assign a hostility value to a target. This input that takes value from 0 for pure friendly targets, 0.5 for unknown targets and 1 for targets that are known to be enemy for sure. Hostility is also another input that also depends on various input parameters and calculation of this hostility value can also be designed using FRBS. Trapezoidal MFs are selected for each input in FRBS defined in Table 5.1. As shown in Figure 5.2, speed MFs defined for Slow, Medium, and Fast are trapezoidal functions tuned for threat spectrum relevant to ADS. After defining the MF for each variable in the decision tree, a set of rules has to be formed that will be used in the fuzzy inference system. Six variables, each with three different values, are used in our FRBS. Considering each variable, fuzzy rules required to obtain for each branch of the decision three shown in Figure 5.1 are equal to the product of the

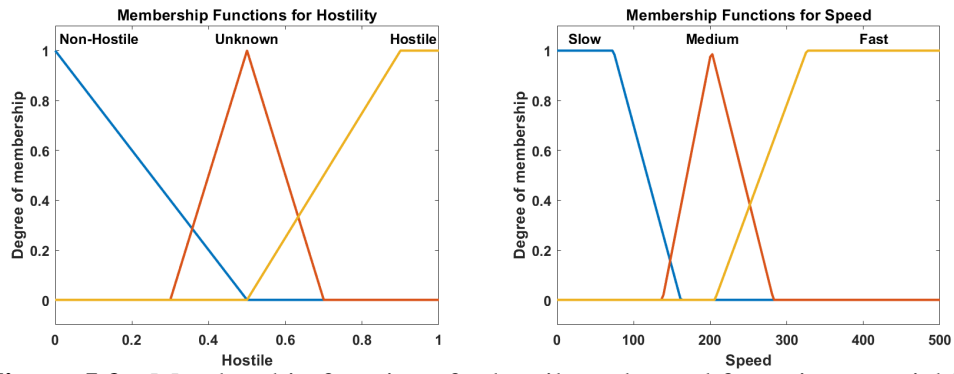


Figure 5.2 : Membership functions for hostile and speed fuzzy input variables.

number of fuzzy values that belong to that branch. In our tree, every branch has three distinct values; hence, the priority value ruleset can have 729 different rules. However, not all of the combinations of ruleset possibilities are feasible, considering the nature of the problem and selected variables. For this study, 127 rulesets are formed for each possible combination of the variables. Table 5.2 shows sample rulesets used for the problem under consideration in this chapter.

Table 5.2 : Sample of fuzzy logic ruleset.

Rule	Hostile	Range to ADS	Time to CPA	Distance to CPA	Speed	Priority
#1	Non-Hostile	Any	Low	Low	Fast	High
#2	Non-Hostile	Low	Any	Any	Slow or Medium	Medium
⋮	⋮	⋮	⋮	⋮	⋮	⋮
#44	Hostile	High	Low	Medium	Medium	Medium
#45	Hostile	High	Low	Medium	Fast	High
⋮	⋮	⋮	⋮	⋮	⋮	⋮
#126	Unknown	High	High	High	Medium	Low
#127	Unknown	High	High	High	Fast	Low

Figure 5.3 shows the surface plot of the change of target priority with two different variables, namely the hostility and range to ADS. It can be seen from the graph the threat degree is low regardless of the hostility of the target for targets at long distances. However, the threat priority increases rapidly if the target is labelled as hostile and increases gradually if labelled as neutral or friend as the threat range to ADS decreases.

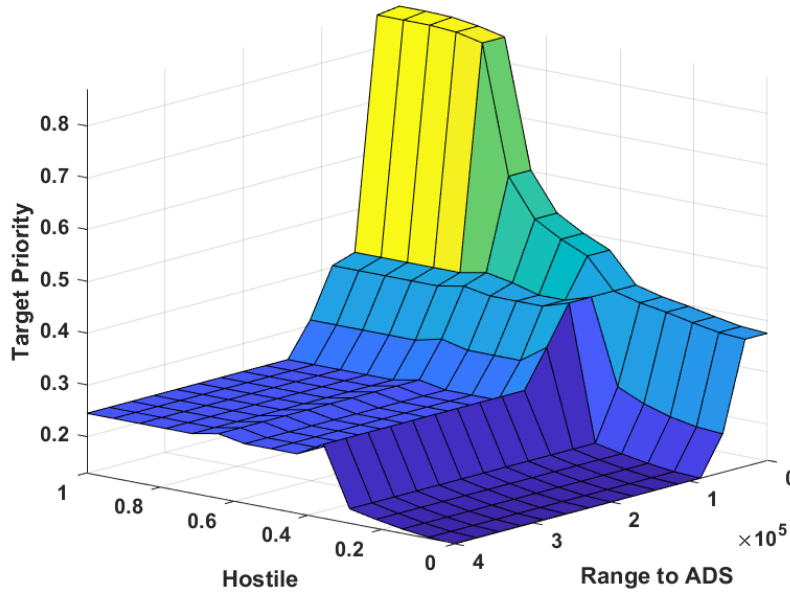


Figure 5.3 : Surface plot of target priority change considering hostility and range to ADS.

Target priority is calculated and updated for each target at every regular time interval. The resultant priority is compared with a threshold to initiate the engagement sequence for targets whose priority exceeds a predetermined threshold. Those targets exceeding the priority threshold are labelled as threats, and the engagement sequence triggers fire control quality tracking in the ADS radar network. Engagement sequence is assumed to be irreversible meaning that once an engagement sequence is initiated, the stopping condition for that target is a successful kill of the threat labeled target or loss of that relevant track.

5.2.2 Optimization method

In the ADS network, fire control radars of ADS are limited in tracking resources and can only track a predetermined number of targets, which is more often limited by design. High-priority threatening targets tend to maneuver and try to break the lock of

fire control radars. Hence, those stressing targets have to be tracked with more than one fire control radar. The tracking accuracy needed for those targets tends to be higher. The tracking requirement for each target can be determined according to the priority. The priority of the targets can be determined using an FRBS, and a threat evaluation process is applied to the targets. After threat evaluation, target tracking requirement η_k^q is assigned to each target according to its priority. Targets that will be engaged are tracked with fire control quality, while others are not. In (5.24) M is the number of targets that the fire control radar is capable of tracking while N is the number of fire control radars in the ADS Network.

$$\begin{aligned} \min_{q=1,2,\dots,Q} & \sqrt{\sum_{q=1}^Q (\mathbb{F}(\mathbf{u}_{i,k}) - \eta_k^q)^2} \\ \text{s.t.} & \begin{cases} \mathbf{u}_{i,k}^q = \{0, 1\} \\ \sum_{i=1}^N \mathbf{u}_{i,k}^q \leq M \end{cases} \end{aligned} \quad (5.24)$$

Binary radar selection parameter u_k presented in (5.24) requires optimization methods that can work with binary variables. Global optimization methods such as pattern search, genetic algorithm, particle swarm, and simulated annealing could be utilized to find the optimal selection parameter. However, real-time solutions to radar selection optimization problems require fast algorithms such as surrogate optimization. A surrogate is an approximation of a function and is utilized mainly for time-consuming objective functions. Surrogate optimization tries to find the global optimum of an objective function using a few evaluations of random selection of sampling points for the objective function. Then, a surrogate of the objective function is created using interpolation of the evaluated points. The next phase of the algorithm searches for a minimum of the objective function by sampling a thousand random points. A merit function based on the surrogate value at these sampled points. The best point is chosen, and the objective function is evaluated at the best candidate point, called the adaptive point. The surrogate is updated using this value, and the algorithm continues with the search again. The surrogate algorithm works well for mixed-integer problems. It fits well to our case of finding the binary selection variable which will provide the selection of radars for the next time period of illumination of ADS fire control radars.

The proposed algorithm for selecting the fire control radars by taking into account target priorities is as follows:

Algorithm 2 Networked FCR RRM algorithm based on target priority

Require: $\mathbf{h}_i(\mathbf{X}_k^q)$: Measurement vector for each target $\forall q = 1, 2, \dots, Q, \forall i = 1, 2, \dots, N$

Ensure: $\mathbf{R}_k$: $[r_1; r_2; \dots; r_Q]$ where $\mathbf{r}_i$ is vector of $1 \times N$ which consists of $[u_{0,k}^q, u_{1,k}^q, \dots, u_{N,k}^q]$

- 1: Set $\mathbf{R}_0 = [1, 0, \dots, 0; 1, 0, \dots, 0, \dots; 1, 0, \dots, 0]$ for initial measurement
 - 2: Obtain first measurements $\mathbf{h}_i(\mathbf{X}_0^q)$: for each target $i = 1, 2, \dots, N$ and $q = 1, 2, \dots, Q$
 - 3: Calculate target priorities Tp_k using FRBS defined in 5.2.1
 - 4: Assign η_k^q for each target depending on target priority calculation Tp_k
 - 5: Obtain radar selection vector $\mathbf{R}_{k+1}$ by solving (5.24) that will be used for next time step $k + 1$
 - 6: Obtain measurement vector $\mathbf{h}_i(\mathbf{X}_k^q)$ for time step k using $\mathbf{R}_k$
 - 7: Fuse measurements in order to obtain target states $\mathbf{X}_k^q$ using output obtained on Step 13
 - 8: Update $\mathbf{J}(\mathbf{X}_{k+1}^q)$ using $\mathbf{R}_{k+1}$ obtained from Step 5
 - 9: Goto Step 10
-

5.2.3 Simulation results

Numerical simulations will be presented in this section to illustrate the effectiveness of the proposed algorithm. A sample scenario with five non-stationary targets and three networked ADSs with phased array fire control radars protecting three DAs is created, shown in Figure 5.4. Radar 1 is located at (0,0) km, Radar 2 is located at (20,0) km and Radar 3 is located at (40,0) km. The locations of the DAs are (10,20) km, (40,15) km and (20,10) km. Target 1, Target 2, Target 3, Target6, and Target 4 are hostile, and Target 5 is labeled as friend. Initial position of targets starting from Target 1 are (20,60) km, (70,30), (−30,40), (30,30), (−20,40) km and (−10,50) km respectively and the initial speed of targets are (0,−250), (−250,−100), (250,−100), (−300,0), (150,−100) m/s and (250,0) m/s. Targets are assumed to follow a constant path, maintaining their initial speed. Considering the defined FRBS, target priority change with respect to time is shown in Figure 5.5. As can be seen from the figure, the priority for the threats increases as they are getting close to defended assets. Although Target 4 heading to the west is hostile, the degree of threat it poses to the defended assets decreases as it passes through the defended assets. Target 5 is a friendly aircraft, so its degree of threat is lowest as it is heading towards the southeast.

After calculating target priorities based on fuzzy logic variables shown in Figure 5.1, targets are evaluated for engagement according to their priority score. Targets labelled as a threats are tracked with fire control quality, and remaining targets are tracked

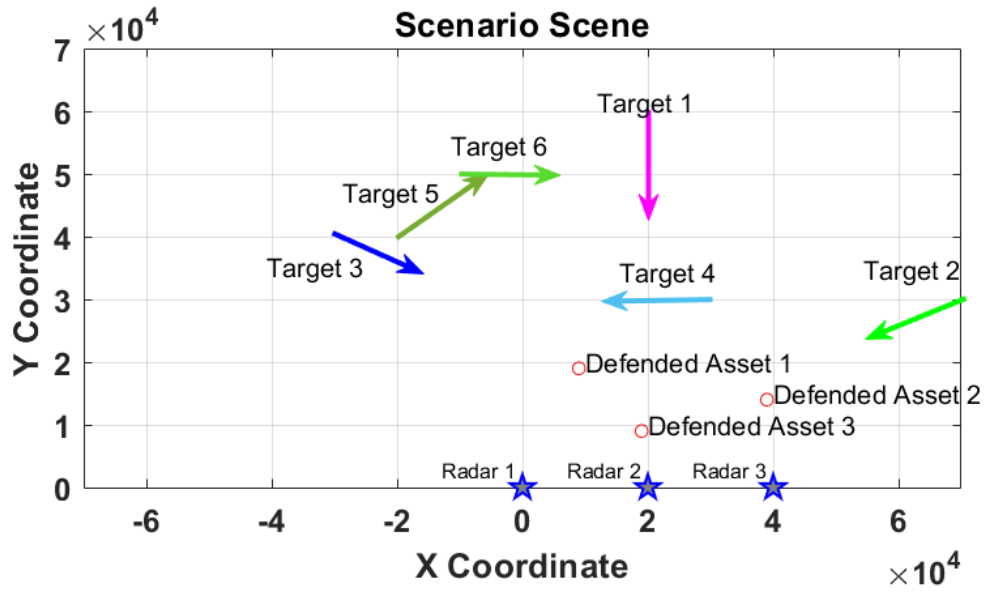


Figure 5.4 : Target scenario.

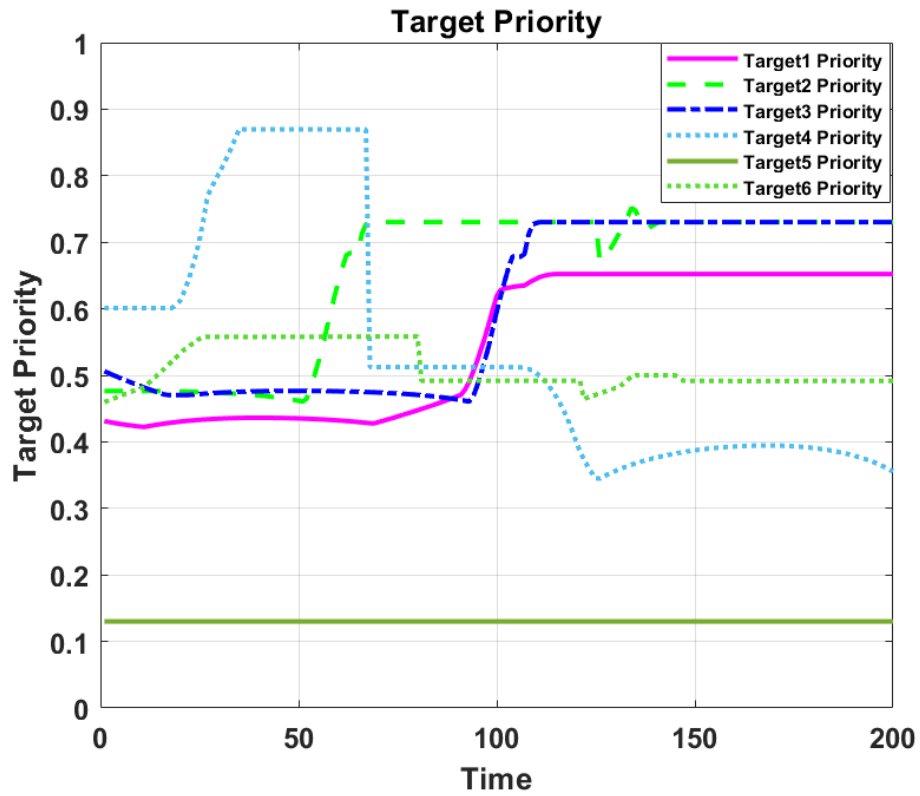


Figure 5.5 : Fuzzy rule-based target priority change.

with surveillance quality to continuously monitor the behaviour for successive threat evaluation. The target priority threshold for labelling targets as threats are selected as 0.7. Each fire control radar defined in the scenario has a maximum tracking capacity of 2 targets. The scenario time for the numerical simulation is 200 seconds.

Target priority calculation and application of adaptive tracking quality metrics to targets are the key processes in the proposed algorithm. To assess the effectiveness of those processes, the proposed algorithm is first run with equal target priorities with a predefined constant target tracking quality metric for each target. The tracking quality goal for the optimization algorithm is set to 3 m for each coordinate for each target. Resultant target truth metrics are plotted using the tracks formed in the fusion center. Figure 5.6 shows truth RMS error in position for the 6 targets in the scenario during the simulation run. It can be seen from the figure that Target 1's and Target 3's RMS errors

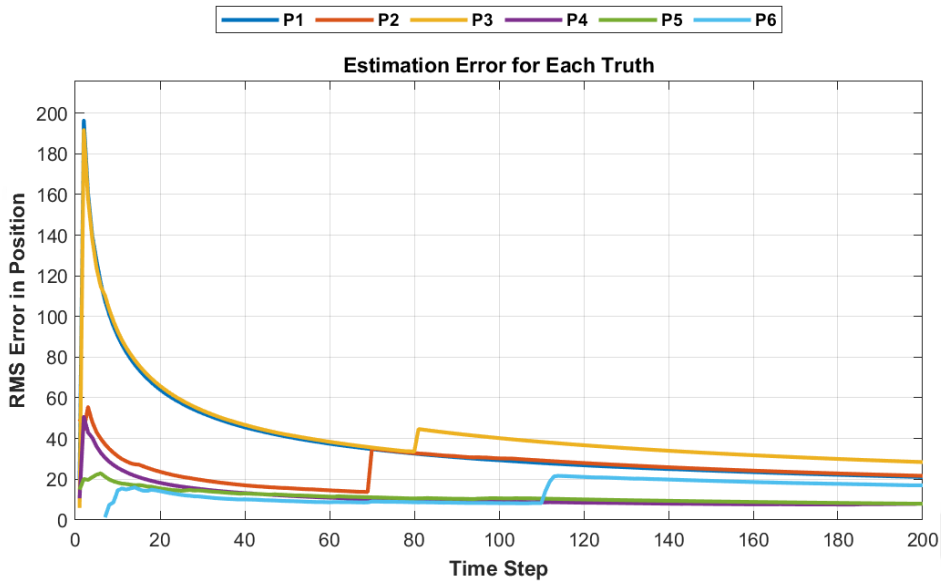


Figure 5.6 : Truth error metrics with target priority disabled working mode.

are higher than the other targets. Because we have 6 targets with different positions and the total tracking capacity of ADS is 6, whenever the optimization algorithm selects 2 radars to track a single target to minimize total error for the optimization objective, this leads to an increase of position RMS error for other untracked targets. The algorithm with equal priority and constant tracking error metric does not take into account friendly and hostile targets. Consequently, friendly Target 5 tracking error is lower than Target 2 and Target 3. Radar selection graphs with respect to time for Target 2, Target 4, and Target 5 are shown in Figures 5.7, 5.8 and 5.9.

Graphs show the selection of radar index during each time instant. The bars' color is shown in blue if a single radar is selected during that time instant, green as two radars are selected, and red as three radars are chosen to track that target. Secondly, proposed algorithm is run using FRBS based priority target determination and adaptive target tracking requirements. Now, targets are prioritized using the FRBS defined in

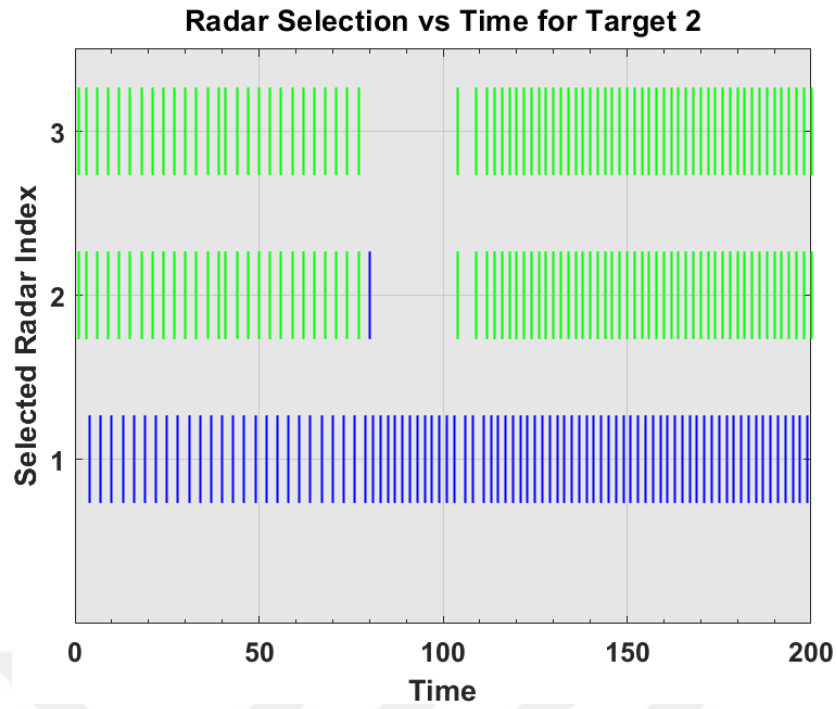


Figure 5.7 : Radar selection for target 2 with priority disabled working mode.

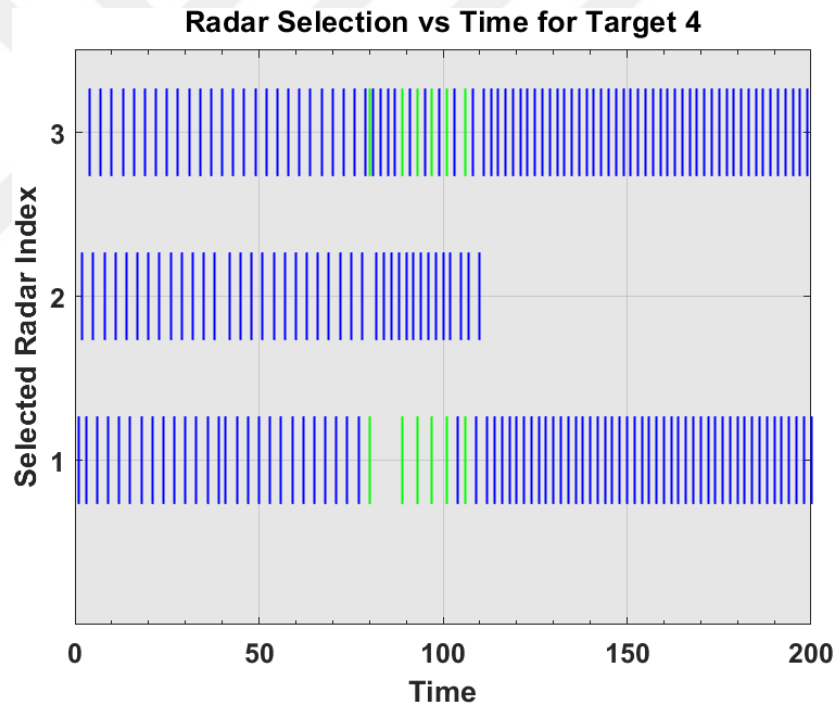


Figure 5.8 : Radar selection for target 4 with priority disabled working mode.

Section 5.2.1. Tracking requirements used for different target priorities are shown in Table 5.3. ADS will engage high-priority targets, so they have to be tracked with fire control quality; on the other hand, lower-priority targets, such as friendly targets, do not have to be tracked precisely, and their tracking error requirement is the lowest. Estimation errors for each truth using these tracking error requirements are shown in Figure 5.10. It is clearly seen that friendly Target 5 RMS error increased as it

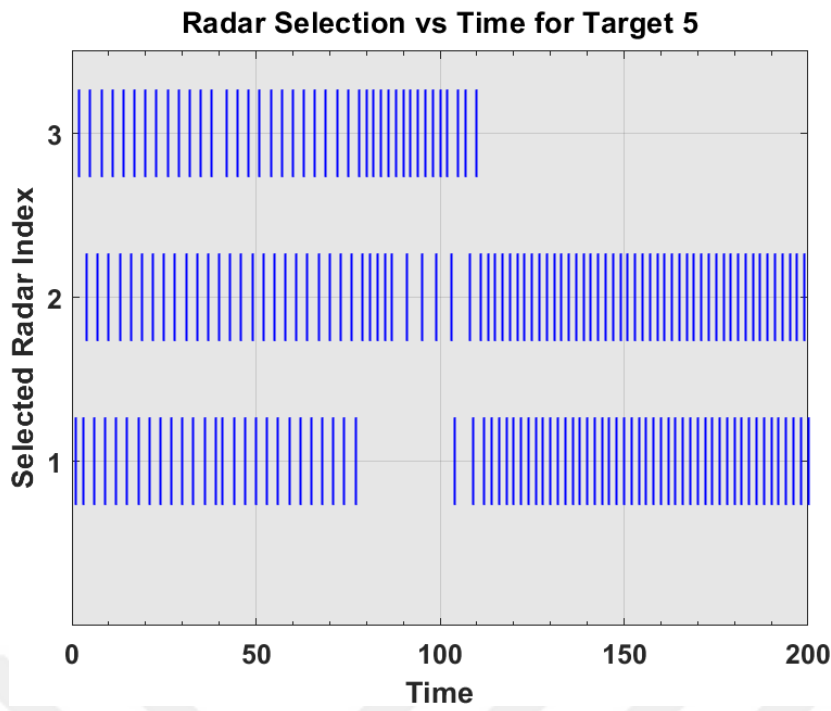


Figure 5.9 : Radar selection for target 5 with priority disabled working mode.

Table 5.3 : Threat priority-based tracking requirement assignment.

Threat Priority	Tracking Requirement (m)
$T_p < 0.3$	100
$0.3 < T_p < 0.5$	10
$0.5 < T_p < 0.6$	7
$0.6 < T_p < 0.7$	5
$T_p > 0.7$	3

has the lowest target priority among other targets. Zoomed estimation error metrics of other targets are shown in Figure 5.11. The figure shows that the RMS error for the targets with high priority decreased dramatically. Radar selection graphs for the second case for Target 2, Target 4, and Target 5 are shown in Figures 5.12, 5.13 and 5.14. It can be seen from radar selection graphs that, taking into account Target 2 priority, leads to an increase in the selection of simultaneous radars. Target 4 priority increases around 20 seconds and reaches its highest value at 35 seconds. Target 4 priority sharply decreases to around 0.51 at 68 seconds, where it stays at this value for around 110 seconds and starts to decrease as the target passes through DAs. It is seen from Figure 5.13 that the increase of priority is reflected in simultaneous radar selection and a decrease after 110 seconds, which is compatible with target priority. It

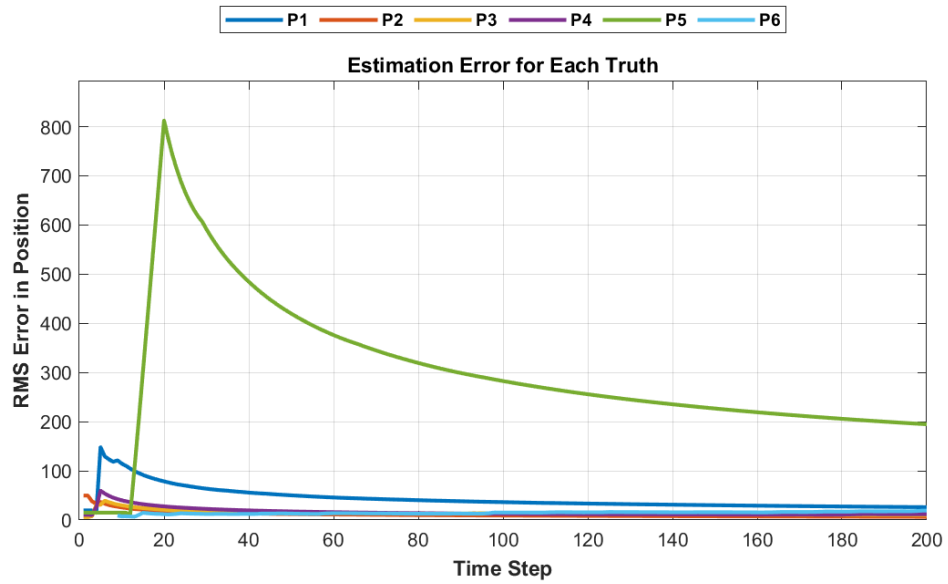


Figure 5.10 : Truth error metrics with target priority enabled working mode (all targets).

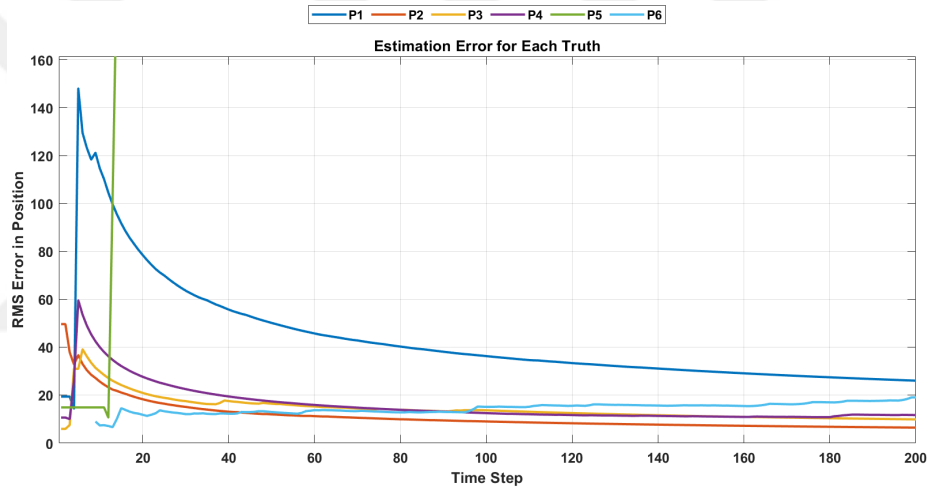


Figure 5.11 : Truth error metrics with target priority enabled working mode (zoomed).

is also seen from Figure 5.14 that for friendly Target 5; the radar selection is rare since the metric is around 100 meters. Table 5.4 summarizes the comparison of cumulative RMS error of optimization results based on equal target priority and equal tracking metric and adaptive tracking metric using FRBS-based threat priority assignment. It can be seen from the table that FRBS-based adaptive tracking leads to a decrease in RMS error values on high-priority targets such as Target 2 and Target 3 and an increase in RMS error for Target 5, which is a friend.

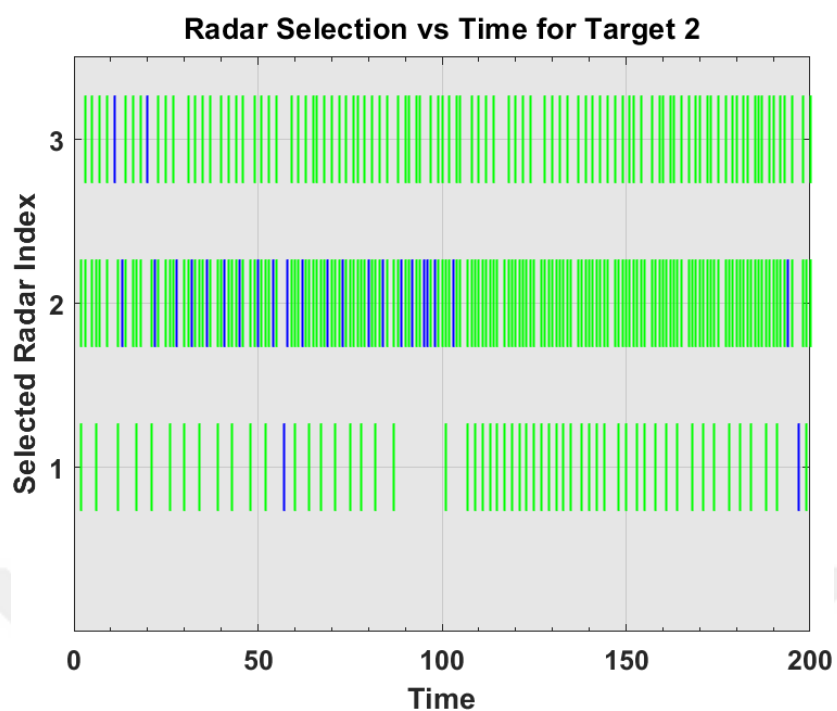


Figure 5.12 : Radar selection for target 2 with priority enabled working mode.

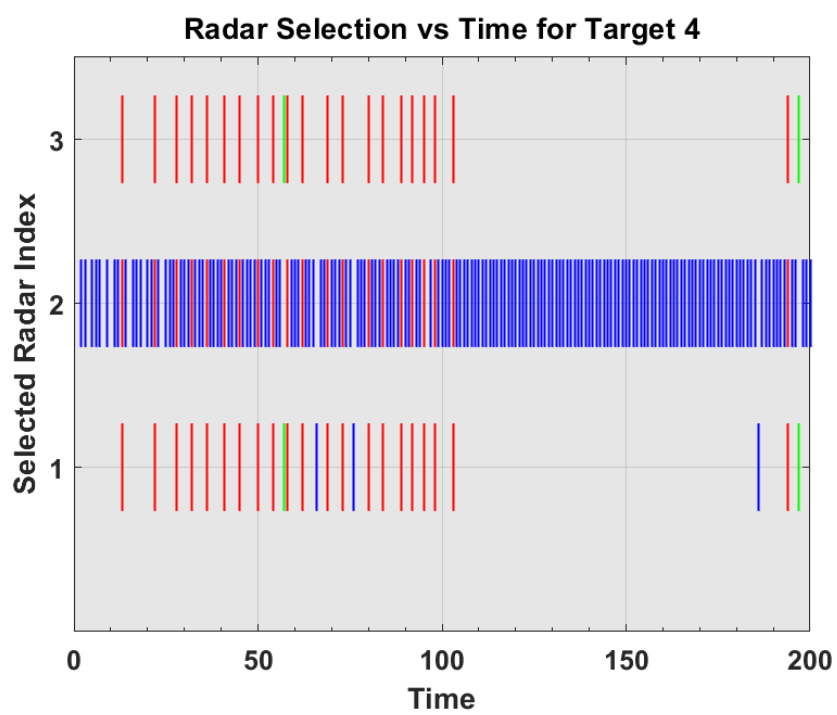


Figure 5.13 : Radar selection for target 4 with priority enabled working mode.

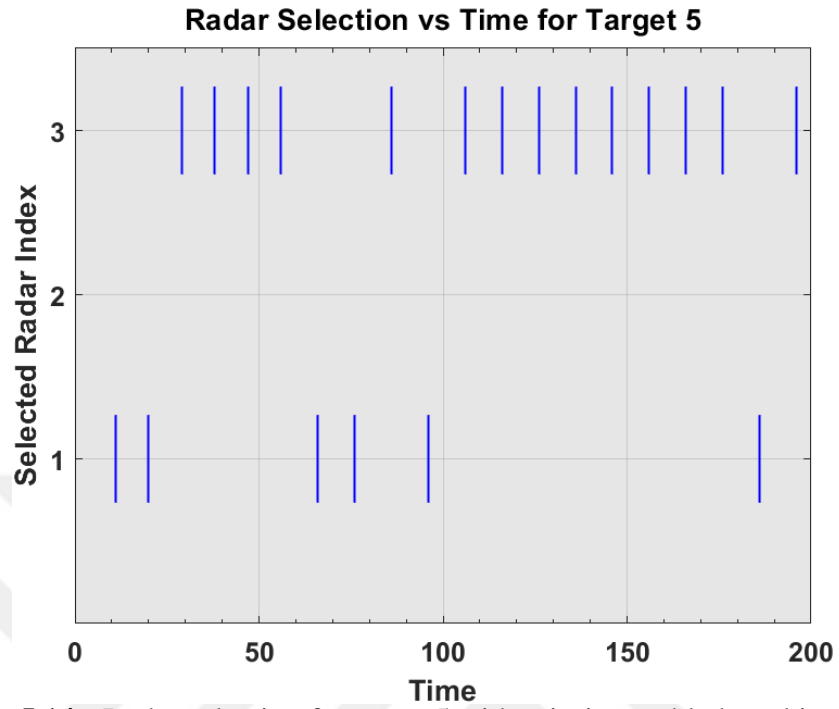


Figure 5.14 : Radar selection for target 5 with priority enabled working mode.

Table 5.4 : Cumulative RMS comparison table.

TruthID	posRMS (m) (Constant Tracking Metric)	posRMS (m) (FRBS Based Adaptive Tracking Metric)
1	21.031	25.986
2	21.624	6.386
3	28.389	9.819
4	7.919	11.628
5	7.897	194.66
6	16.958	18.993

5.3 Case Study-2: Networked Air Defense Radar Resource Management Under Power and Tracking Constraints

Ground-based air defense systems (GBAD) are designed to protect air space and defend assets from aerial threats. Aerial threats span a wide range, from low, small, slow, cheap targets such as drones to much more expensive high-speed targets such as hypersonic missiles. Utilizing large numbers of those threats in a coordinated way combined with the electronic warfare capabilities of the adversary pushes or even exceeds the limits of the capability of air defense systems [118]. Multifunction phased array radar (MPAR), used to search, track, and classify targets, is the primary sensor of these systems and is extensively affected by evolving threat environments where saturation attacks are utilized. Networking these air defense system radars is a solution to decreasing the tracking load, allowing more targets to be tracked, increasing the search capability, and decreasing the track initiation time [121].

The performance of GBAD is guaranteed when the MPAR provides the tracking quality (TQ) needed for its engagement operations. However, the radar resource left for tracking functionality determines the capacity of the radar to track multiple targets with needed engagement TQ. The TQ depends on both the illumination time on the target and the transmitted power of the MPAR. Increasing the illumination time for tracking reduces the available time for other radar functions such as surveillance; on the other hand, increasing transmitted power leads to improved signal-to-noise ratio (SNR), coming with the cost of increased detectability of the radars in the network. Thus, to allow time for radar functions other than tracking and decrease the detectability of the network radars, the tracking load and transmit power can be distributed between the radar nodes. Several studies have been performed to distribute tracking load according to the required TQ. Adaptive tracking is a technique that can be used to track targets according to their needed TQ according to the target priority, and its usage is shown in single radar [122] as well as in radar networks [123] [121].

The power allocation problem falls into two main categories. The first category tries to maximize the overall or the worst tracking accuracy for all targets with a limited power [34, 40, 124]. The second category minimises the overall power budget to

achieve the required target tracking capacity [125, 126]. Minimizing transmit power to achieve certain tracking or detection performance requirements has been studied for radar networks in [127–130]. The beam selection and power allocation for C-MIMO radar network has been studied in [130] to achieve the required constant tracking quality. Cooperative node selection and transmit resources such as dwell time, transmit power and effective bandwidth assignment problem are investigated in [131]. The study limits the number of selected radars with an upper limit; however, it does not limit the total number of targets a single radar can track simultaneously.

Existing work on radar network resource management does not consider a dynamic tracking quality requirement determined by target priority under the constraints of the target-tracking capacity of a single radar under total transmit power limitation. The solution to this problem is valuable for MPAR, which is used in air defense networks that work mainly in saturation conditions. This paper proposes a networked radar resource management algorithm that utilizes distributed target tracking and transmit power optimization based on target priority to select the optimal number of radars and their transmit power with constraints on total transmit output power and tracking resources. The algorithm tries to solve the objective function against the tracking and transmit power constraints using surrogate optimization and tries to achieve the required TQ for each target in the network by minimizing the distance between the trace of the predicted Bayesian Cramér-Rao Lower Bound (BCRLB) and the assigned TQ for each target according to target priority.

5.3.1 Radar transmit power and tracking constraints

The MPAR resources used in ADS limit the maximum number of targets tracked for engagement operations. Even though the priority of the tracking task dedicated to engagement operations is higher than that of the surveillance tasks, when the number of targets increases, MPAR has to degrade its surveillance capacity to cope with the challenging resource assignment problem. Lower priority targets, such as friendly or hostile targets far from the engagement boundary, do not need to be tracked at engagement quality. Thus, resources can be managed according to different performance requirements. Another resource that has to be managed is the transmit power in an MPAR. The peak transmit power determines the maximum detection

range. However, the targets at various ranges with different target priorities do not need to be tracked at full power according to their required TQ. Adjusting the transmit power according to the TQ decreases the detection probability of an MPAR. The detectability decreases further if the transmit power is distributed through the networked radars. This section will first examine the effect of transmit power limitation on MPAR performance. Next, the factors affecting the maximum number of targets an MPAR can track will be given.

5.3.1.1 Effect of transmit power constraint on multifunction phased array radar performance

To understand the role of transmit power in radar operation, we have to look at parameters affecting the signal-to-noise ratio (SNR). The SNR formula for the radar is given in the following equation.

$$SNR = \frac{P_r}{P_n} = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 R^4 k T_0 F B} \quad (5.25)$$

Where

- P_r : Received power,
- P_t : Transmitted power of radar,
- P_n : Noise Power,
- G_t, G_r : Transmit and receive antenna gain,
- λ : Wavelength of radar,
- σ : RCS of target,
- k : Boltzmann Constant,
- T_0 : Receiving system noise temperature,
- B : Bandwidth of the matched filter for the radar's transmitted waveform,
- F : Noise factor of radar receiver,
- R : Distance from radar to target.

The variance of the range and bearing information are related to the SNR of the received target echo. In a phased array radar, variance of the range is related to SNR by,

$$\sigma_R = \frac{\nabla R}{\sqrt{2 SNR}} = \frac{c}{2B\sqrt{2 SNR}} \quad (5.26)$$

Variance of the bearing is also related to SNR with

$$\sigma_\theta = \frac{\theta}{k_m \sqrt{2 SNR}} \quad (5.27)$$

As seen from Equation (5.26) and Equation (5.27), increasing the SNR decreases the range and bearing measurement error. From Equation (5.25), increasing the transmitted power P_t increases the SNR, thus improving the range and bearing measurement errors. The improved range and bearing measurement error leads to an improvement in the TQ of the targets. However, target TQ requirements can be compromised if the ADS does not engage the target. The TQ requirements of the targets can be set according to their target priority. This can put a lower bound on the transmit power of MPAR to achieve the required tracking accuracy. Setting above this level increases the chance of the MPAR's detectability by adversaries' electronic warfare capabilities. In a networked ADS that utilizes MPAR, the transmit power can be lowered with distributed tracking of the targets within the network. Variations in power allocation affect system performance beyond minimizing detectability, such as reducing power requirements for platforms with limited power resources and increasing the robustness of the platforms due to decreased operating temperatures. Using high power continuously can lead to excessive heat buildup in the transmitter components. This may result in premature ageing or failure of the transmitter, reducing the radar's overall longevity.

5.3.2 Target tracking capacity for phased array radar

The target tracking capacity of an MPAR is affected by the restrictions posed on pulse duration ratio, radar time, computing resources, and range ambiguity [132]. The MPAR resources shall be minimized for tracking each target to increase the maximum tracking capacity. The maximum number of targets an MPAR can track is the minimum of the constraints imposed by the long pulse period ratio and the radar time, range unambiguity constraint, and computer constraint [133].

The constraints of the long-period pulse duration ratio and the radar time limit the maximum target number, such as;

$$N_{max1} = \frac{1}{\gamma} \cdot \frac{(P_t \cdot D_L - \bar{E}_s)}{R^4 \cdot SNR_{0opt}} \cdot \frac{\bar{T}_{opt}}{\bar{N}_{opt}} \cdot \frac{\cos^2 \alpha_p \cdot \cos^2 \beta_p}{N_{PRT}} \quad (5.28)$$

Where

$$\gamma = \frac{(4\pi)^3 \cdot k \cdot T_0 \cdot L_s \cdot N_F}{G_t \cdot G_r \cdot \sigma \cdot \lambda^2} \quad (5.29)$$

and

- D_L : Long period pulse duration ratio permitted by radar,
- $\bar{E}_s$: Radiated energy used for searching,
- $\bar{T}_{opt}$: Optimum frame time period,
- SNR_{0opt} : Optimum SNR in the direction of the maximum gain,
- α_p, β_p : Prediction angles of the tracked target,
- N_{Topt} : Optimum value of the average illuminating times required for updating a target,
- N_{PRT} : Number of pulses in one dwell time.

The maximum target number from the range unambiguity constraint can be calculated as follows;

$$N_{max2} = \frac{150 \times 10^3 \cdot \bar{T}_{opt}}{\bar{N}_T \cdot (R + 150 \times 10^3 \cdot t_b)} \quad (5.30)$$

Where

- $\bar{N}_T$: The average sampling period for tracking,
- t_b : The radar non-operating time.

The last constraint comes from the computer processing power that can be calculated as;

$$N_{max3} = \frac{\bar{T}_{opt} \cdot (1 - T_{BACK})}{\bar{N}_{Topt} \cdot T_{PRO}} \quad (5.31)$$

Where

- $\bar{T}_{PRO}$: The computer time for processing a single tracking,
- T_{BACK} : The computer time for processing all kinds of other tasks.

The maximum number of targets N_{max} is limited by the minimum of these constraints, which is,

$$N_{max} = \min(N_{max1}, N_{max2}, N_{max3}). \quad (5.32)$$

ADS's fire control radar (FCR) shall track targets with the quality needed for successful engagement. The design of the FCR is optimized to maximize the number of simultaneous engagements it can support. When MPAR executes both surveillance and tracking tasks, engaged targets can be tracked at fire control quality, and the other targets can be tracked at lower track quality. The limitation for a single MPAR can also be overcome by distributing the engagement and surveillance task load to other MPARs on the network with abundant radar resources.

5.3.3 Proposed networked radar resource management method

The resource management problem of networked MPAR FCR, which has power and tracking limitations in an air defense network, can be solved by distributing the tracking load to networked radars. The distribution of the tracking tasks along the

network also has the side benefit of lowering the radars' transmit power, which reduces their detectability. While distributing the tracking load to the network, this resource management method shall also guarantee that the TQ requirements for engagement operations are satisfied. The constraints and objectives of the optimization problem are first given before proceeding to the solution approach. Lastly, the solution approach is provided with the algorithm pseudocode.

5.3.4 Constraints and objectives

The optimization objective for this problem is to achieve the tracking requirement for each target q at each time instant k under the radar network's power and tracking limitations. The required TQ is η_k^q , and N_{max} is the maximum number of targets each radar in the network with n radars can track with the engagement quality. Each radar in the network has a maximum transmit power, which is given by P_{max} and a minimum transmit power constraint stated by P_{min} . $u_{i,k}^q$ is the binary variable which indicates that the i th radar is selected to track the q th target at time instant k . The total transmit power of the network is also constrained with P_{Total} , which is a limitation that comes from reducing the emission from the networked radar. Equation (5.33) summarizes the objective and the constraints of the networked radar resource management problem for a radar network with tracking and power limitations.

$$\begin{aligned} & \min_{q=1,2,\dots,Q} \sqrt{\sum_{q=1}^Q (\mathbb{E}(u_{i,k}^q) - \eta_k^q)^2} \\ & \text{s.t.} \begin{cases} u_{i,k}^q = \{0, 1\} \\ P_{min} < p_{i,k}^q < P_{max} \\ \sum_{i=1}^n u_{i,k}^q \leq n * N_{max} \\ \sum_{i=1}^n p_{i,k}^q u_{i,k}^q \leq P_{Total} \end{cases} \end{aligned} \quad (5.33)$$

5.3.5 Solution to the resource management problem

The optimization problem stated in Equation (5.33) tries to find both the selected radars (nodes) at each time instant with a maximum total number of tracking target constraints and also the transmit power allocated to each radar chosen to satisfy the total transmit power limitation. The objective function defined in Equation (5.33) is used in the optimization algorithm to achieve the required TQ for each target in the

network by minimizing the distance between the trace of the predicted BCRLB and the assigned TQ. The radar selection vector and the assigned transmit power shall be found to minimize this objective function with the tracking and power limitation constraints.

The surrogate optimization algorithm is selected to solve this mixed-integer global optimization problem. Surrogate model-based optimization is a methodology that uses surrogate modelling techniques to find quickly the local or global optima [134]. Surrogate models approximate complex simulation models, allowing faster simulation and optimization [135]. The speed advantages provided by surrogate models have enabled these models to be used in the field of the defence industry. In [136], surrogate models are used to optimize the deployment of combat systems of systems in a short time. The application of surrogate models for networked radar optimization problems has also been shown in [56]. Surrogate models can handle non-convex and multi-modal functions more effectively than traditional optimization algorithms such as gradient descent or evolutionary algorithms, which improves the chance of finding global optimum in complex problems. The design of the surrogate models can be done to balance exploration by trying new, untested regions and exploitation by focusing on promising regions. Acquisition functions such as expected improvement or probability of improvement are used to guide the optimization process by suggesting where to sample next based on the surrogate model.

After initialization of the radars in the network and the fusion center, the radars operate with initial operating conditions. The initial operating conditions can be a selection of all radars with full transmit power to increase the detection probability of the targets within the tracking boundary of the networked radars. The associated TQ is assigned to the targets according to their priority Tp_k^q . The target priority can be calculated using a Fuzzy Rule-Based System, which considers the features of the target, such as speed, heading, and range. Thus, η_k^q is a function of Tp_k^q that can be a step function that assigns predefined tracking qualities to certain target priority level intervals. The optimization problem in Equation 5.33 is solved to find the optimization variables of the radar selection vector and the transmit power associated with each selected radar. Then, the networked radars are operated with these parameters. The following detections from the networked radars are associated with the existing tracks

using GNN, and the unassociated detections are used to form new candidate tracks in the fusion center. Using these tracks, the predicted BFIM is calculated for the next cycle. Predicted BCRLB is computed using the trace of BFIM. This computation is used in the optimization routine in the following cycle to find the following operating parameters of the networked radar.

Algorithm 3 shows the pseudocode of the proposed method.

Algorithm 3 Networked RRM under power and tracking constraints.

- 1: Initialize Radar Operating Parameters
 - 2: Initialize Tracker and EKF Filter
 - 3: Initialize FCR TaskList
 - 4: Initialize Optimization Variables
 - 5: Initialize Lower and Upper Bounds for Optimization Variables
 - 6: Operate Radars with the initial $u_{i,0}^q$ and $p_{i,0}^q$
 - 7: Form initial Tracks with first measurement vector
 - 8: **while** RadarNetworkOperates at each time step k **do**
 - 9: Calculate Target Priorities Tp_k^q according to target features
 - 10: Assign TQ Metric η_k^q according to calculated
 - Target Priorities Tp_k^q
 - 11: Solve (5.33) to find $u_{i,k}^q$ and $p_{i,k}^q$ according to assigned
 - TQ Metric η_k^q
 - 12: Operate selected radars $u_{i,k}^q$ with the calculated transmit
 - power $p_{i,k}^q$
 - 13: Obtain measurement vector $\mathbf{z}_{i,k}^q$ from network radars
 - 14: Associate detections to Tracks using the GNN Algorithm
 - 15: Update target state vector $\mathbf{x}_k^q$ using measurement obtained
 - on Step 13
 - 16: Form new Tracks for the unassociated detections
 - 17: Update $\mathbf{J}(\mathbf{x}_{k+1}^q)$ using Equation (5.13)
 - 18: Calculate $\mathbf{C}_{k+1|k}^q$ using Equation (5.19)
 - 19: Calculate $\mathbb{F}(u_{i,k}^q)$ using Equation (5.20)
 - 20: Goto Step 10
 - 21: **end while**
-

5.3.6 Simulation results

A scenario with 16 targets is set up to understand the effectiveness of the proposed radar resource management algorithm for networked radars under power and tracking constraints. The scenario consists of three MPARs, which are located at (0,0) km, (20,0) km, and (40,0) km, and three defended assets that are located at (10,20) km, (40, 15) km, and (20, 10) km. All radars are identical with the technical parameters shown in Table 5.5.

Table 5.5 : Radar technical parameters.

Parameter	Symbol	Value
Maximum Tracking Capability	$N_{\max}$	3
Maximum Transmit Power	$P_{\max}$	300kW
Minimum Transmit Power	$P_{\min}$	10kW
Minimum Total Transmit Power	P_{Total}	300kW
Maximum Range	R_{Max}	100 km
Operating Frequency	F_{Op}	3 Ghz
Number of Pulses in Dwell Time	N_{PRT}	10

The simulation scenario is shown in Figure 5.15. The targets have a constant velocity with varying speeds. They are distributed to have inbound, outbound and crossing trajectories. Inbound targets heading to defended assets, as well as air defense radars, have higher target priorities than outbound targets. The required TQ is set according to the target priority T_p as shown in Table 5.6. It is assumed that ADS engages the targets with a priority higher than 0.7; thus, they have the highest requirement for TQ.

Table 5.6 : Target TQ requirement according to target priority.

Target Priority	TQ Requirement
$0 \leq T_p < 0.3$	100 m
$0.3 \leq T_p < 0.5$	10 m
$0.6 \leq T_p < 0.7$	5 m
$0.7 \leq T_p < 1$	3 m

The MATLAB R2023a global optimization toolbox surrogate algorithm was used to solve the optimization problem. MATLAB's surrogate optimization routine builds a surrogate model based on an initial set of sampled points and their values, approximating the actual objective function. This model is usually a Gaussian Process (GP) or Kriging model. Gaussian processes are primarily used in surrogate modelling since they estimate both the function value at the sampled point and the prediction's variance at that point. After the surrogate model is built, an acquisition function is used to decide the next sampling point to explore regions with high uncertainty and focus on improvement areas. The algorithm selects the next point to sample using the acquisition function and evaluates the objective function at the next sampling point. This new function output is added as new data to the training set for the surrogate model. This process is repeated until a stopping condition such as a maximum number of iterations, convergence based on the improvement in function value or a target

objective function value is met. The complexity of this optimization algorithm depends on the number of function evaluations and the dimensions of the decision variables. Although the surrogate optimization computational complexity is $O(N^3)$, it is more efficient than brute force methods with expensive objective functions.

Firstly, the algorithm proposed in Algorithm 3 is run without the power limitation, which only considers a maximum number of target tracking limitation constraints for the radar network. The graphs are shown for constant TQ requirements and changing TQ requirements based on target priority according to Table 5.6.

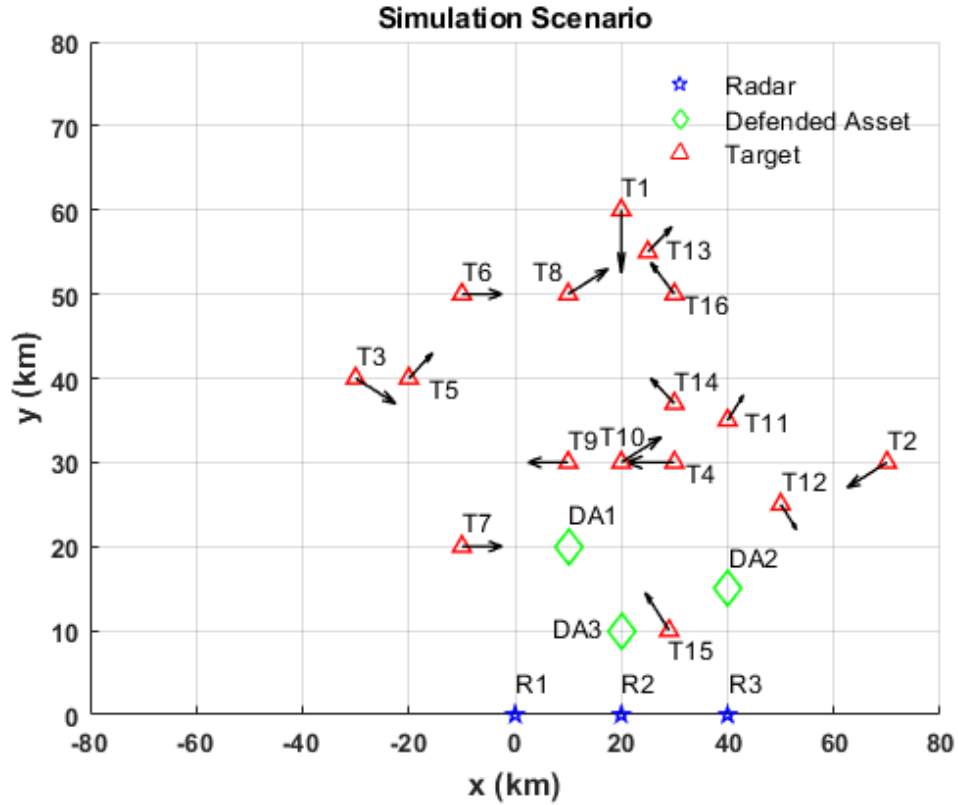


Figure 5.15 : Simulation scenario.

The priority of the target is expected to increase when the target is inbound and targeting the defended assets or our radars. Also, we expect the target priority to decrease when the target is outbound and moving away from the defended assets and the radars; the priority of the target decreases. Target 3 and Target 5 are candidate targets that fit into these descriptions. The tracking priorities and the corresponding TQ requirement of these targets are shown in Figure 5.16. The priority of Target 3 starts with a value of 0.5 and decreases a little as the target moves, and after a while, target priority increases above 0.7. This priority will initiate the engagement sequence

of the networked ADS, and the TQ will be at the highest level, as shown in Table 5.6. Target 5 is far away from the defended assets and heading away from them. So, the priority is close to 0.1 and stays at the lowest assigned level until the scenario ends. The selected radars versus time index will be investigated with the assigned transmit

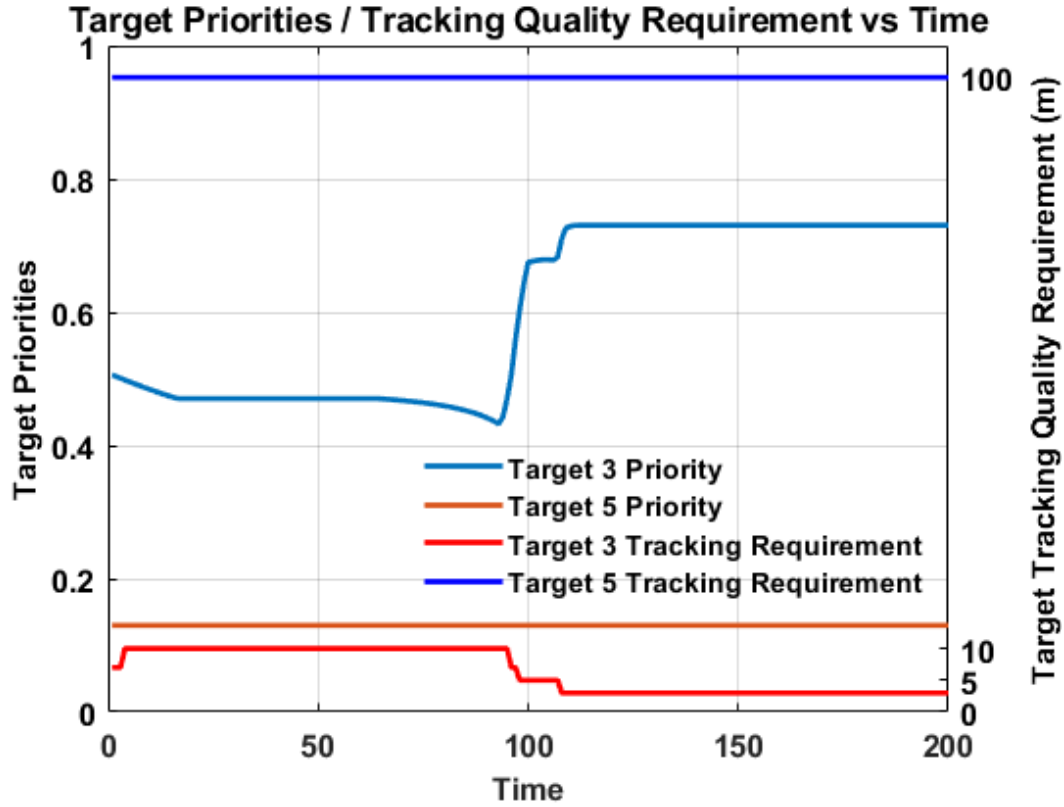


Figure 5.16 : Target priorities and TQ requirement for target 3 and target 5.

power output when we optimize the transmit resources only, as well as both transmit and power constraints to the radar network for these targets. Figure 5.17 shows the assignment of the radars for constant TQ of 3 m for each target with full transmit power output from the networked radars for Target 3. According to the optimization results, as seen from Figure 5.17, the first radar was selected more often than the other radars,

Figure 5.18 shows the radar selection graph for Target 3 in the radar network and the assigned transmit power when the algorithm is run with transmit power limitation and maximum target tracking constraint. When the power and tracking constraints are optimized according to target priority, it can be seen from Figure 5.19 that the number of selected radars increases during the whole simulation to compensate for the transmit power limitation. Also, there is a decrease in the transmit power when

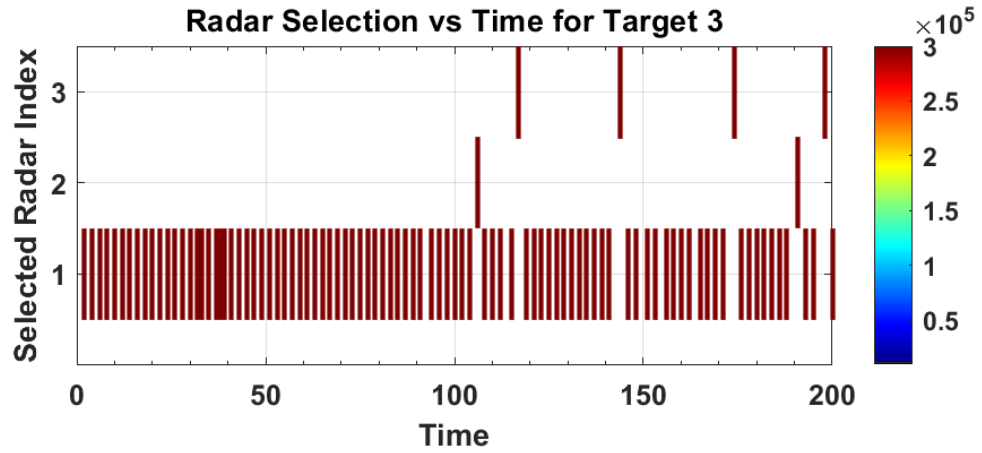


Figure 5.17 : Target 3 radar selection results (Constant TQ and full transmit power).

the target priority is below 0.5 and an increase in the transmit power when the target priority is above 0.7 after 100 seconds.

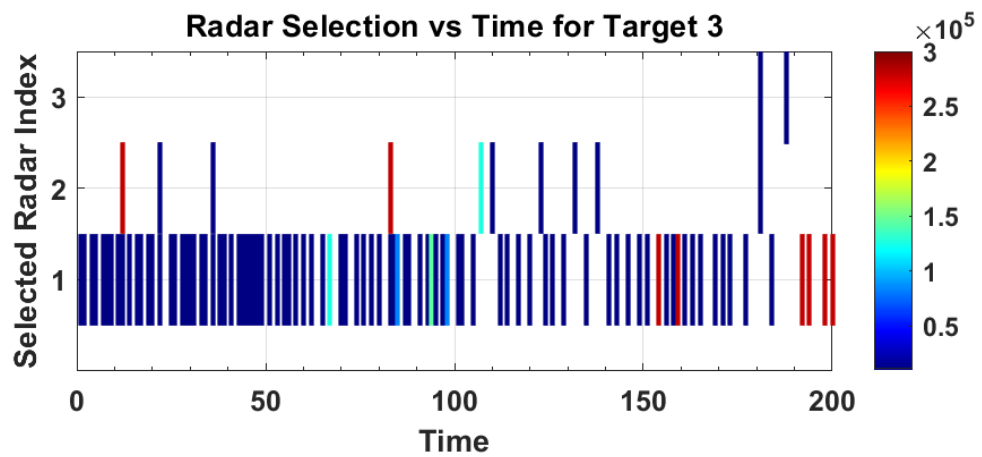


Figure 5.18 : Target 3 radar selection results (Constant TQ and transmit power limitation).

The effect of the optimization algorithm on radar resources can be seen much more clearly for Target 5 in the simulation, which is a low-priority target. Figure 5.20 shows the radar selection graphs with full transmit power and with a maximum number of target tracking constraint.

Figure 5.21 shows the radar selection graph and the assigned transmit power when we run the algorithm with additional transmit power limitation.

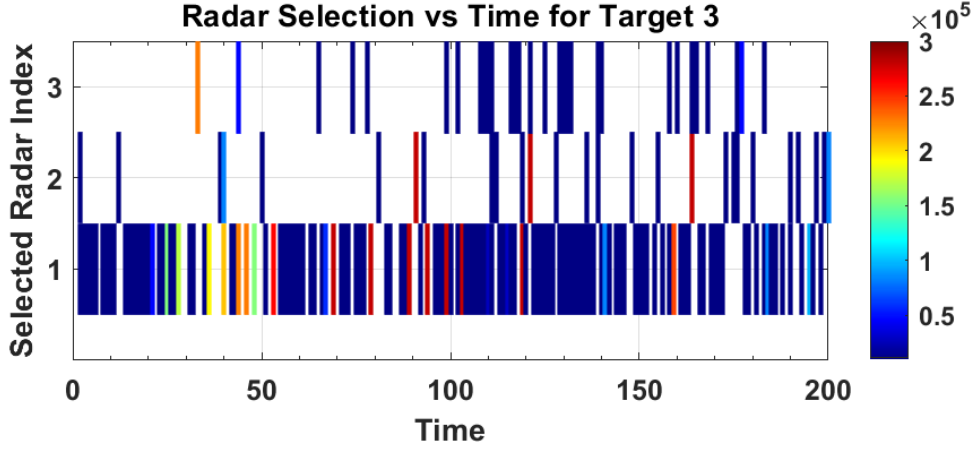


Figure 5.19 : Target 3 Radar selection results (Target priority based TQ and transmit power limitation).

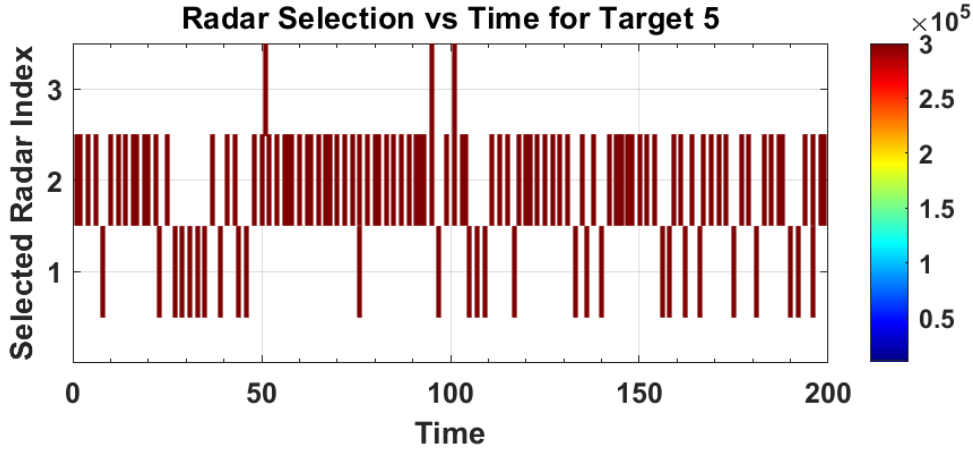


Figure 5.20 : Target 5 radar selection results (Constant TQ and full transmit power).

As we include target priority-based TQ constraint in the resource management algorithm, it can be seen from Figure 5.22 that the number of selected radars and the assigned transmit power for each selected radar has significantly reduced according to required TQ.

The constraints in the optimization Algorithm 3 are varied according to different cases to understand the added benefit of the proposed radar resource management method for networked air defense radars. The definition of each case is given in Table 5.7. Case 1 corresponds to constant track quality without transmit power limitation, and Case 4 corresponds to target priority based track quality requirement as defined in Table 5.6 and limitation of transmit power according to Equation 5.33.

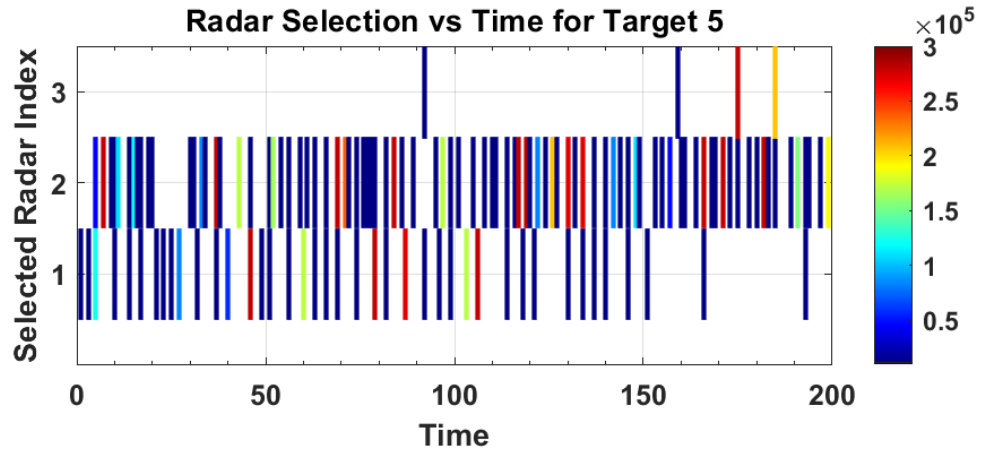


Figure 5.21 : Target 5 radar selection results (Constant TQ and transmit power limitation).

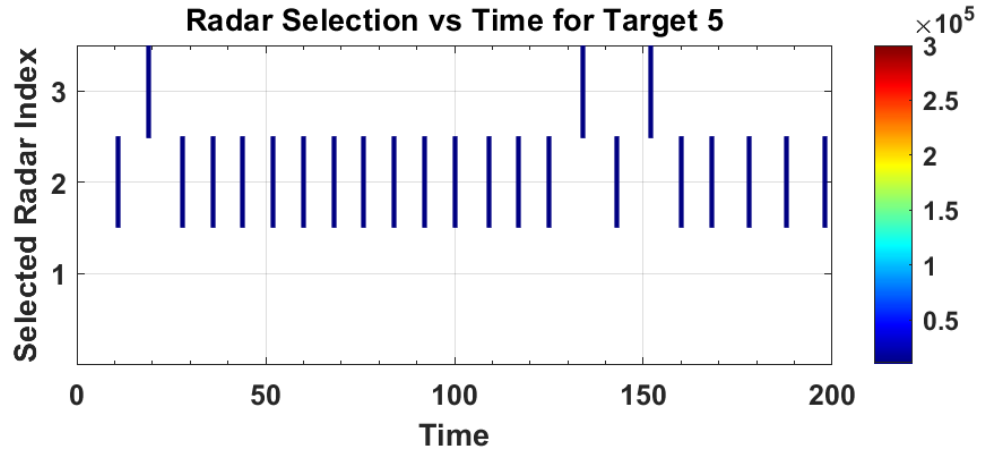


Figure 5.22 : Target 5 radar selection results (Target priority based TQ and transmit power limitation).

Table 5.7 : Description of different cases.

Cases	Definition
Case 1	Constant TQ, Full Transmit Power
Case 2	Target Priority Based TQ, Full Transmit Power
Case 3	Constant TQ, Transmit Power Limitation
Case 4	Target Priority Based TQ, Transmit Power Limitation

The total transmit power of Radar 1 in the simulation is shown in Figure 5.23 for different cases. This graph clearly shows that the total transmit power for Radar 1 is reduced when target priority is considered, even though the radars are working with full power. When there is a total constraint on the total power, but the TQ requirements

are kept constant, total transmit power decreases. If the radar is operated with target priority based TQ requirements and transmit power constraints, the transmit power decreases even more.

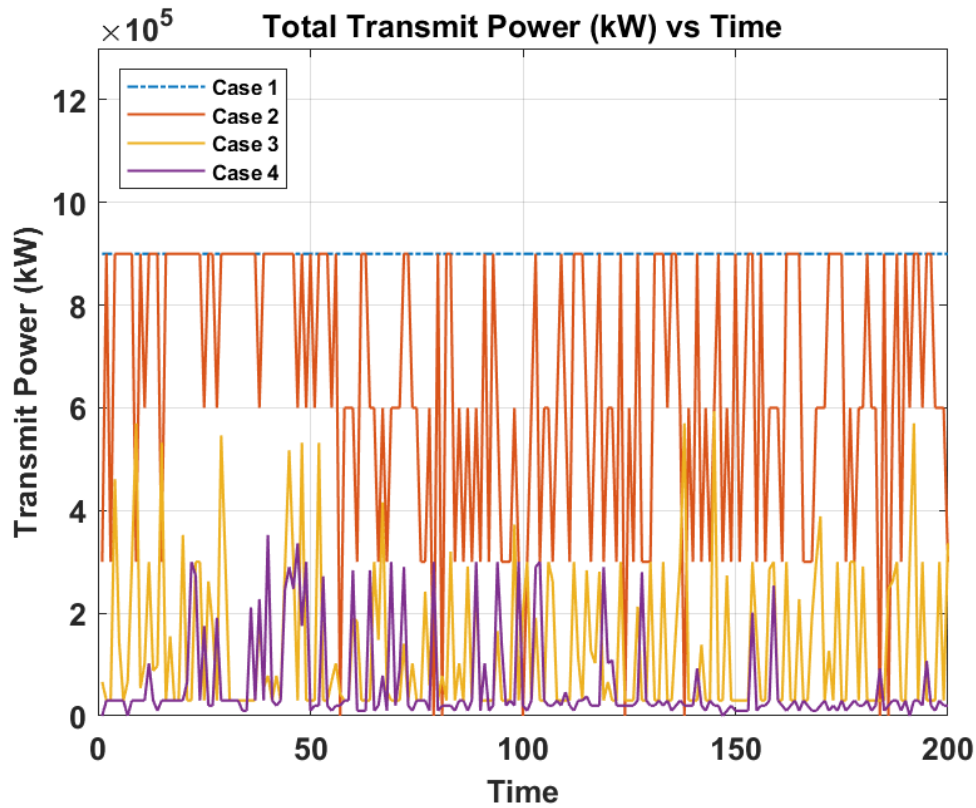


Figure 5.23 : Radar 1 transmit power vs time for different modes of operation.

The average power of each radar in the simulation for each radar in the network is summarized in Table 5.8. The average transmit power is reduced when the radar resource management algorithm considers both TQ constraints according to target priority and transmit power constraints, including maximum transmit power limitation and total power limitation. Figure 5.23 and Table 5.8 clearly show the expected benefit of the proposed algorithm considering maximum transmit power and total transmit power limitation constraints.

Table 5.8 : Average transmit power for radars in the network.

Cases	Radar 1 (kW)	Radar 2 (kW)	Radar 3 (kW)
Case 1	900,000	900,000	898,500
Case 2	640,500	699,000	627,000
Case 3	134,607	95,906	130,171
Case 4	60,282	31,814	37,996

Next, the result of constraints on the transmit power and maximum tracking capacity will be examined by looking at the requested BCRLB and calculated BCRLB values for sample cases. Figure 5.24 shows the target and calculated BCRLB values for Target 3. It can be seen from the graph that track priority-based tracking quality with full transmit power performs better than the other cases. Due to saturation conditions of the radars under the maximum number of tracking constraints, full transmit power with constant tracking quality case fails to achieve the requested BCRLB value. For the target priority-based tracking quality with transmit power limitation case, even though the calculated BCRLB fails to achieve the requested BCRLB at the beginning of the simulation, it almost achieves the requested BCRLB after 100 seconds.

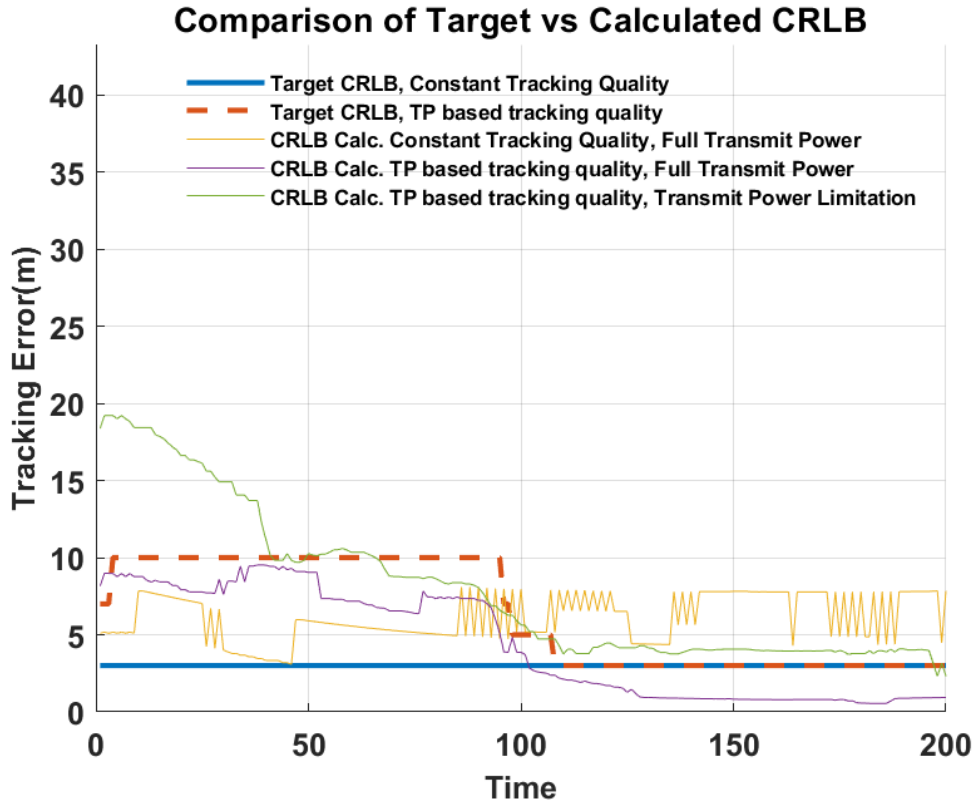


Figure 5.24 : Comparison of requested BCRLB vs calculated BCRLB target 3.

Figure 5.25 shows the situation for Target 5. Since this target is a low-priority target during the simulation, the requested tracking quality is 100 m. For target priority-based tracking requirements, cases with and without power limitations satisfy the upper limit. Considering target priority-based tracking quality requirements in the optimization routine will free up additional resources for tracking other targets in the scenario. For full transmit power and constant tracking quality requirement of 3 m during the whole simulation time case, the calculated BCRLB is slightly above the requested BCRLB,

indicating excessive usage of resources for a low-priority target that does not need this level of high-quality tracking.

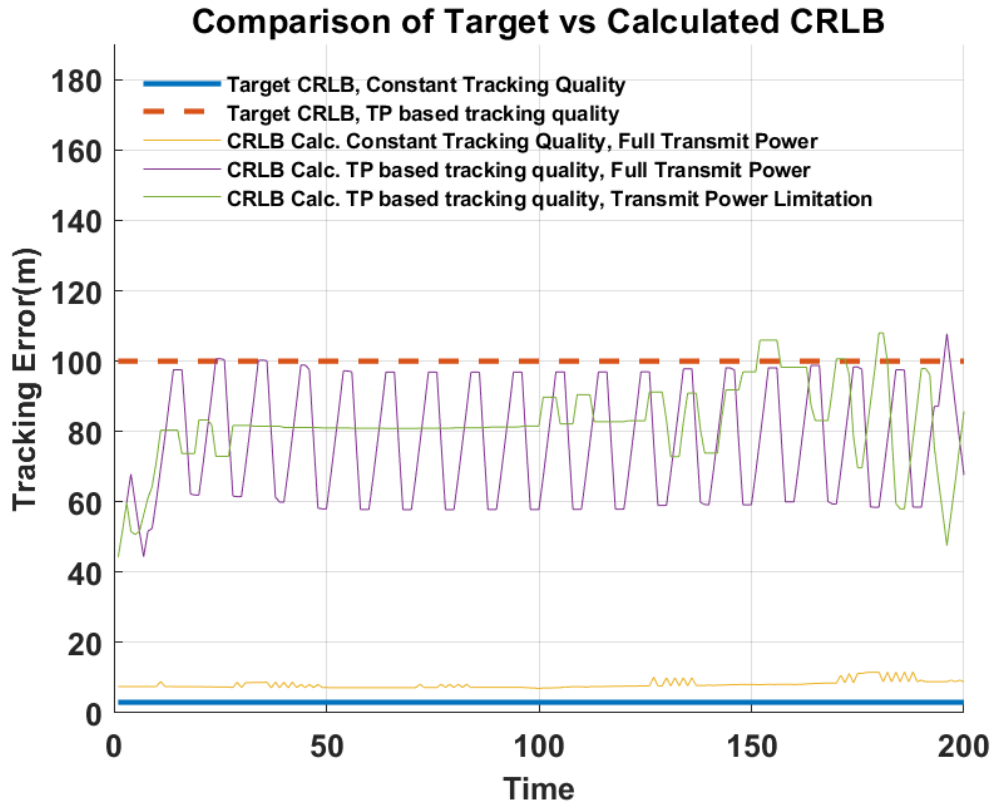


Figure 5.25 : Comparison of requested BCRLB vs calculated BCRLB target 5.

The RMSE for each target in the scenario is summarized in Table 5.9. The mean value at the end of the table indicates that the algorithm achieves close results between Case 2 and Case 4. This performance is achieved by selecting more radars in Case 4 while satisfying the maximum target tracking capacity of the air defense radars while reducing the transmit power of those radars. Case 1 is the best performance achieved as expected. Case 3 performs better at the simulation mean values than Case 2 and Case 4. However, this comparison considers the entire simulation time for the targets, which has priorities change over time, which might be misleading for high-priority targets that have to be tracked at a tracking requirement needed for engagement.

The targets are engaged in the air defense network when the target priorities are higher than 0.7. It will be more meaningful for the RMSE values for the simulation times where the targets have a priority higher than 0.7. Table 5.9 summarizes the mean values of different cases under engagement conditions. This table indicates that Case 1 and Case 4 achieve similar results under engagement conditions, while Case 2 and

Table 5.9 : RMSE (m) for targets in different cases.

Target No	Case 1 (m)	Case 2 (m)	Case 3 (m)	Case 4 (m)
Target 1	4.422	28.046	9.284	22.767
Target 2	4.677	2.332	13.117	16.534
Target 3	4.045	2.610	10.768	3.117
Target 4	4.396	20.862	13.057	14.644
Target 5	6.545	49.991	14.983	39.328
Target 6	4.164	2.262	10.513	3.972
Target 7	5.936	13.737	14.459	31.909
Target 8	4.728	34.600	18.054	28.468
Target 9	5.491	32.702	16.489	28.544
Target 10	5.132	37.713	14.740	26.132
Target 11	5.873	49.230	16.375	40.660
Target 12	5.726	23.135	16.795	30.255
Target 13	6.344	50.771	17.829	42.224
Target 14	6.054	41.492	16.935	43.727
Target 15	6.731	5.779	13.852	23.413
Target 16	6.892	50.161	17.813	45.254
Mean	5.447	27.839	14.691	27.559

Case 3 have higher RMSE values under engagement conditions. Considering both the results of Table 5.9 and Table 5.10, it can be seen that the proposed algorithm performs almost the same or even better than the full transmit power case with equal target tracking requirement that is needed for air defense engagement.

Table 5.10 : Mean RMSE (m) for engagement cases.

Case 1 (m)	Case 2 (m)	Case 3 (m)	Case 4 (m)
3.413	26.002	43.098	3.612

5.4 Summary and Discussion

In this work, we propose a novel networked radar resource management algorithm by adaptively tracking targets in a ADS network using target priority assessment based target tracking quality requirement assignment as a first case study. An FRBS, which also considers parameters related to the protection of defended assets for the whole network, is utilized to prioritize the targets in the ADS network. FRBS is used to calculate target priorities to assign the tracking requirement for each target dynamically. The tracking capacity of each fire control radar in the network is also taken as a constraint to the optimization algorithm in the ADS network. The proposed

algorithm selects fire control radars that will track the highest priority targets for the next time frame under these constraints. The algorithm is run with and without the target prioritization to compare the performances. Results show that the proposed algorithm decreases the RMS estimation error for high-priority threatening targets in a networked ADS. In future work, more control parameters, such as power and dwell time of the radars, will be considered in the networked ADS radar resource management optimization problem. As a second case; a networked radar resource management algorithm has been proposed for networked air defense MPAR which has both tracking and transmit power constraints. The proposed algorithm is compared with different cases, including a baseline case with no transmit power limitation and constant target tracking quality requirement for each target in a simulation scenario with saturation conditions. The results of the simulation show that the proposed radar resource management algorithm selects more radars while satisfying each radar's maximum target tracking capacity under transmit power limitation conditions. This lowers the overall transmit power of the radar network, which has the added benefit of increased survivability and robustness due to less heat buildup in the transmitter components. The air defense network needs to track targets at the engagement quality when the target is threatening the defended assets. At other times, the targets can be tracked with less tracking quality without reducing too many radar resources, which may lead to track loss. The simulation results show that the tracking quality at engagement conditions performs similarly to unconstrained cases under saturation conditions. At the same time, the air defense resources are optimized according to the proposed networked radar resource management algorithm for air defense networks.

6. CONCLUSIONS AND RECOMMENDATIONS

The importance of ground-based air defense systems is increasing with the proliferation of air threats. Increasing air space protection via ADS requires deploying multiple long-range systems on the battlefield. However, these systems have limited radar and interceptor resources, which sometimes restrict the systems' contribution to overall air space protection. Today's battlefield requires netted operations to increase resilience, provide a common operational picture, and share information and resources needed by the network participants. This leads to the concept of networked air defense systems that cooperate to increase air defense protection. The MPAR used in these air defense systems has beam agility, which allows the time-sharing of resources when needed by the network participants, particularly in saturation conditions. The sharing of radar resources also has the benefit of tracking highly maneuverable targets with low target signatures, and it also decreases emissions by distributing the transmission to netted radars to enhance the survivability of the air defense systems. Unlike resource management of individual radars, resource management of network-based radars deals with macro-scale resource management over wider time intervals.

In this thesis, radar resource management algorithms for multifunction phased array radars used in networked air defense systems are developed. The algorithms developed in this thesis primarily depend on the target priority obtained using FRBS. FRBS is proven to reflect expert knowledge and is known for ease of implementation. However, the extraction of the rules and adaptation of the system to the changing operational environment is challenging and needs automation to reduce the workload of the warfighter. Thus, we developed a novel methodology for air defense systems to extract the fuzzy rules and to adapt the FRBS to the changing operational environment using GFS. Operator experience collected from surveys applied to expert operators is used to train fuzzy rules for different operational contexts. Then, the DSS adapts to the changing operational environment using the input provided by the operators. The feasibility of the proposed methodology is shown by conducting a sample survey of

two groups of air defense operators. Since air defense operations primarily engage higher priority targets, a custom cost function emphasizes higher threat priority output errors. Numerical analysis has shown that using the custom cost function reduces RMSE for higher threat priority levels at the expense of an increase in lower threat priority results, which is believed to be acceptable in air defense operations. The proposed methodology in this thesis can be applied as an automated FRBS threat evaluation in netted air defense systems.

Developed radar resource management algorithms are presented in two consecutive chapters. An RRM for networked air defense system radars is presented in Chapter 4, which relies on adaptive tracking of the targets according to their maneuver and priority. Adaptive tracking is beneficial for air defense systems since targets tracked by the ADS fire control radar tend to maneuver to break the tracking lock to eliminate the following engagement. With adaptive tracking, the tracking rate of the radar is increased to keep the quality of the target track necessary for engagement operations. Thus, along with the IMM filtering, increasing the tracking rate by utilizing an adaptive tracking rate avoids tracking loss of maneuvering targets. The developed algorithm utilizes the maneuver detection of the network to trigger a shared adaptive tracking of the target by the fire control radars of the network. Simulation studies have shown that sharing resources within the networked radars decreases tracking occupancy, leaving room for search operations and thus decreasing the frame time. Also, the added benefit of sharing resources decreases the track initiation time of the targets, thereby enlarging the engagement timeline of the ADSs, which finally increases the effectiveness of air defense provided by ADSs.

Algorithms presented in Chapter 5 rely on optimization techniques based on target priority for networked radars. Two cases are studied. One of the case relies on selection of minimum number of radars required for achieving tracking accuracy determined for particular target priority levels. BCRLB is selected for performance metric and the optimization problem tries to select the minimum number of radars required to achieve the requested tracking quality. Numerical simulation studies have been done for two modes of operation: target priority-enabled and disabled modes. The results of the simulation studies proved that the algorithm reduces the resource utilization of the networked radars while preserving the requested tracking quality

for targets to be engaged. In the second case, the networked radars are optimized under tracking and transmit power constraints. The tracking limitation comes from the capacity of fire control radars while transmit power is limited in cases where low observability is required. This limitation also has the benefit to heating of transmitter elements on the radars which increases the robustness. This algorithm is also simulated under saturation conditions and proved that the required tracking quality requirement is preserved with the total number of target tracking constraints with reduced total transmit power output.

As a future work, additional control parameters of the networked radars such as bandwidth, dwell time, waveform can be added to the resource management problem of the networked fire control radars of ADS which aim to satisfy target tracking quality requirements for high priority targets to be engaged. Fast, real time working Q-RAM algorithms based on QoS algorithms can also be studied for MPAR radar resource management to increase networked air defense system effectiveness.



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