Fault-tolerant Radio Coverage and Connectivity in Wireless Mesh Networks

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Zusammenfassung

Drahtlose Mesh-Netzwerke sind eine spezielle Netzwerkinfrastruktur, die ausschließlich drahtlose Verbindungen nutzt. Der Backbone wird durch drahtlose Multi-Hop-Verbindungen, d.h. Verbindungen mit mehreren Zwischenstationen, gebildet. Die mobilen Stationen nutzen im Gegensatz zu klassischen Drahtlosnetzwerken nicht eine sondern mehrere Drahtlosverbindungen zu Netzwerk-Backbone. Damit bieten Mesh-Netzwerke mehr Flexibilität und mehr Ausfallsicherheit im Vergleich zu klassischen Funknetzwerken mit drahtgebundener Infrastruktur.

Werden Mesh-Netzwerke in dynamischen Umgebungen (z.B. Produktion und Logistik) eingesetzt, so können Änderungen der Umgebung (z.B. neue Hindernisse) die Funkkommunikation stören. Dies betrifft sowohl die Funkabdeckung, als auch die Konnektivität innerhalb des gesamten Mesh-Netzwerkes.

Der Beitrag dieser Dissertation ist ein Fehlertoleranzverfahren zur Sicherstellung der Verfügbarkeit der Dienste Funkabdeckung und Konnektivität eines Mesh-Netzwerkes in dynamischen Umgebungen. Im Normalzustand haben die Dienste hinreichend Redundanz, um die Fehlerursache (fault) Umgebungsdynamik zu tolerieren. Das Auftreten von Umgebungsdynamik führt zu einem Fehlerzustand (error). In diesem Zustand werden die Dienste korrekt erbracht, die Redundanz ist aber nicht mehr gegeben. Das entwickelte Verfahren erkennt die Fehlerzustände und behebt sie, bevor sie zu einem Versagen (failure) der Dienste führen. Diese Fehlerbehebung stellt die Redundanzeigenschaft der Dienste wieder her.

Für die Fehlererkennung und –behebung wurden Verfahren für die Modellierung der Radiowellenausbreitung sowie zur Anpassung der Modelle an die Realität durch Referenzmessungen und Lokalisierung von Netzknoten entwickelt. Für die Fehlerbehebung wurden effiziente Optimierungsverfahren entwickelt, die mit einem Minimum an Kosten und Laufzeit eine Kommunikationsinfrastruktur mit hinreichender Dienstqualität bestimmen.

Die Evaluation in verschiedenen industriellen Umgebungen hat gezeigt, dass die Fehlererkennung zuverlässig die Fehlerzustände erkennt und die Fehlerbehebung effektiv die Redundanz wiederherstellt. Damit garantiert das entwickelte Verfahren die Verfügbarkeit der Funkabdeckung und Konnektivität von drahtlosen Mesh-Netzwerken in dynamischen Umgebungen.

Abstract

Wireless Mesh Network is a special network infrastructure which uses only wireless connections. The network is wireless multi-hop, meaning that the connections possibly include multiple intermediate stations. The lack of a wired backbone promises more flexibility, compared to classic infrastructure networks.

When wireless mesh networks are used in dynamic propagation environments (e.g. manufacturing, logistics), the changes in the environment (e.g. new obstacles) can disturb the wireless communication. This affects both the radio coverage and the connectivity of the network. The radio coverage ensures that the mobile stations can connect to the network while they are within a service area. The connectivity ensures that the network topology is connected.

This dissertation contributes a fault-tolerance method for guaranteeing the availability of radio coverage and connectivity of wireless mesh networks in dynamic propagation environments. The services in normal state have a redundancy, tolerating the fault *environmental dynamics*. The occurrence of faults lead to error state of the services. In this state the service is still correct, because of the initial redundancy, but the redundancy is lost. Our method avoids the failures by detecting the error states and performing system recovery before an error leads to failure. The system recovery restores the original redundancy of the services.

We have developed new methods for *error detection* and *system recovery* which are required for radio coverage and connectivity of wireless mesh networks. The error detection and system recovery are especially challenging in dynamic propagation environments. For this purpose we have developed a new method for *automatic radio model calibration*. This method uses measurements from the network to adapt a radio propagation model to the real environment. The measurements are obtained in an automatic way from the infrastructure and from a new *localization* service, developed specifically for this purpose. Based on the calibrated model our error detection method detects the dynamics in the propagation environment. Based on the model and a new *automatic base station planning algorithm,* our system recovery method restores the normal state of the services.

The evaluation in different office and industrial environments has shown that the error detection method successfully detects the errors and the system recovery method successfully restores the normal state of the service. This guarantees the availability of radio coverage and connectivity of wireless mesh networks in dynamic propagation environments.

Acknowledgement

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Contents

1. Introduction

In this dissertation, we consider the challenges of guaranteeing the availability of *radio coverage* and *connectivity* of *wireless mesh networks* in *dynamic propagation environments*. Radio coverage and connectivity are basic network services, ensuring the communication. The dynamic environment and the requirements for high availability and self-maintainability make this task challenging.

1.1. Radio Coverage and Connectivity in Wireless Mesh Networks

Wireless Mesh Network (WMN) is an ad-hoc network with a fixed network infrastructure (see an example in figure 1.1 on the following page). The physical structure of a WMN includes base stations, a backbone and mobile stations. The *base stations* (also known as mesh routers or mesh points) are static wireless nodes, forming the network infrastructure and providing wireless network access to the mobile stations. The *backbone* is a wireless ad-hoc network among the base stations. The fixed network infrastructure provides wireless network access to the mobile stations in a service area. *Service area* is a finite three-dimensional space. The *mobile stations* are wireless nodes which move within the service area and communicate to other stations via the WMN. The stations in a WMN use a *multi-hop routing protocol* for communication. This protocol automatically discovers the network topology and delivers the messages to the destination; if needed over multiple hops. We can think of a WMN as an infrastructure wireless network in which the backbone is replaced by a wireless one and the communication is done in a (multi-hop) ad-hoc way.

We consider a wireless mesh network which supports a business process and is under the administration of an organization. This is not a MANET (Mobile Ad-hoc Network) consisting of self-dependent mobile nodes, like it is often in the literature. The organization has control over the network infrastructure and aims at providing radio coverage and connectivity in a clearly defined service area. The *management appliance* is a central instance for basic configuration and diagnosis of the WMN, including topology monitoring, protocol settings, traffic management, etc.

Radio coverage and *connectivity* are basic *services* of a wireless mesh network which are required for communication. Radio coverage ensures that the mobile stations can

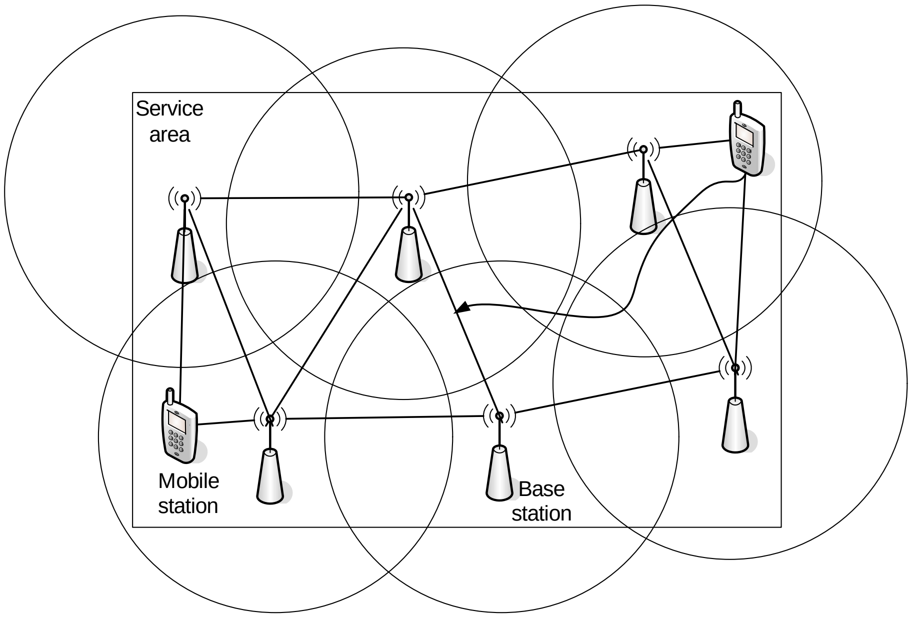


Figure 1.1.: Wireless mesh networks and radio coverage

access the network infrastructure (backbone) while they are located or moving in the service area. Connectivity ensures that the topology of the backbone is connected.

Radio coverage

The service *radio coverage* is *correct*, if the service area is *covered* by the base stations. The service area is covered, if the unification of radio cells of all base stations contains the whole service area. The radio cell of a base station is a part of the space around it, in which a mobile station observes the base station with a radio signal strength sufficient for communication. The sufficient radio signal strength in the service area is a basic requirement for the mobile stations to be able to access the WMN. The radio coverage service ensures this sufficient signal strength in the service area. Service location is a point of the service area, specified by its coordinates. A service location is covered, if the unification of radio cells of all base stations contains the service location.

Connectivity

The service *connectivity* is correct, if the backbone graph is connected. The *backbone graph* is a graph with the base stations as vertices and the routing layer links among them as edges. A *link* exists if two wireless devices can communicate through the wireless medium obeying some qualitative parameters (see section 5.3 for more information). The backbone graph represents the network topology at the routing layer. This graph is connected, if a *path* (a sequence of edges) exists between every two vertices. A connected backbone graph means a connected routing layer topology which is a basic requirement for communication through the WMN. The connectivity service ensures that the backbone graph is connected.

At the example WMN in figure 1.1 the radio coverage and the connectivity are correct. The unification of radio cells contains the service area and the backbone graph is connected.

1.2. Motivating Application Scenario

In this section, we will discuss the usage of wireless mesh networks in an industrial automation application scenario. We will consider the advantages of WMN in such scenarios but also the typical operating conditions in these scenarios. This will give us insight on defining the requirements and constraints for radio coverage and connectivity in the next section.

Advantages of wireless mesh networks for automation The broad use of wireless networks in the consumer sector makes them makes them more appealing for industrial automation scenarios. Firstly, they provide a transparent mobile extension of the wired Ethernet which is broadly used in automation scenarios. Secondly, there is a good knowledge on the advantages and the possible pitfalls, since the WLAN technology has been used in the consumer sector for many years. Last but not least, the mass market of the consumer sector leads to decreasing product prices. The use of wireless networks in automation enables many new applications; which optimize the production process. In all these applications, providing wireless connectivity to the mobile entities, ensures more detailed and up-to-date supervision and diagnosis, more flexible control and improved scalability [101]. This leads to a better integration which is a clear trend in the manufacturing automation [112].

The Wireless Mesh Networks are more promising. They are similar to the infrastructure networks but promise flexibility, self-organization and seamless mobility. WMN offer flexibility because no wires are required for the backbone network. The network can be easily deployed and reconfigured. WMN have a self-organizing topology. When a crash of a base station occurs, it can be automatically repaired by re-routing. The ad-hoc communication means that the mobile stations are connected to the wireless network through multiple communication links. As the mobile stations move, they gradually obtain links to new base stations and loose links to remote base stations. In this sense, the mobile stations always remain connected to the network. They do not perform roaming as in the classic infrastructure networks. This is an important advantage for real-time control applications.

The evolution of manufacturing We consider an industrial automation application scenario. The scenario consists of a production hall with production lines, machines and material handling systems which carry out an automated process. Traditionally, the production systems have used (and many of them still use) *dedicated manufacturing lines* (DML). DML are fixed production lines which are able to produce a specific part (engine, etc) which is the main production good of a company. Since DML are designed for fixed functionality, they have a simple design and they are optimized for a maximum production capacity which is also fixed [81].

However, a clear trend is visible, from dedicated manufacturing lines to changeable and reconfigurable manufacturing systems [60]. This trend is driven by the market, demanding lower costs and customized goods in smaller production batches [74, 136]. The traditional DML can not meet these demands. In a dynamic demand situation, they are either underutilized, or can not meet either the required product variation or the needed production capacity.

The *flexible manufacturing systems* (FMS) address these challenges. FMS consist of computer-controlled programmable automation devices and can produce a variety of parts on the same system [80]. The programmable automation devices are complex machines, robots, etc; which are able to perform different tasks. They are controlled by a central control unit to perform the operations, needed for a specific variation of the product. Since FMS contain complex, multi-purpose automation devices, they are more expensive and slower than DML. Many systems today use the FMS paradigm. However, this paradigm is reaching its limits. The reason is that the current manufacturing systems need to be responsive. Responsiveness is the ability of a manufacturing system to quickly and cost-effectively adapt to product changes, governmental regulations and component failures.

A cost-effective responsiveness requires a combination of the benefits of DML and FMS. The answer is *reconfigurable manufacturing systems* (RMS).

Reconfigurable Manufacturing Systems (RMS) is a well established production paradigm in the manufacturing systems community [56, 60, 81, 80, 105]. A RMS is a system with adjustable structure, that is able to meet the market requirements with respect to capacity, functionality, and cost. The adjustable structure is at system level and at machine level. The system level adjustments include "adding, removing or modifying machine modules, machines, cells, material handling units and/or complete lines" [60]. This includes, for instance, flexible storage and material handling systems [131]. The system level adjustments are a relocation of machinery, facilities, and goods within the production hall. The machine level adjustment includes changes in the hardware and software components of the machines.

The trend to reconfigurable manufacturing systems is supported and driven by international foundations and platforms; for instance, the NSF Engineering Research

Center for Reconfigurable Manufacturing Systems [34] and the European Technology Platform “Manufacture” [30].

Another example in adaptable manufacturing is the research project WdmF which is funded by the German Federal Ministry of Education and Research [32]. The project consortium includes famous manufacturing companies from different sectors (e.g. automotive, aerospace). The project has developed methods for modular factory design. A prototype of a modular factory has been realized and the project results have been published in a book [141]. Papers in established manufacturing journals show the clear trend to reconfigurable manufacturing systems [140].

The challenge: high availability in dynamic environments Using wireless communication in the presented industrial applications and environments poses some tough challenges. These challenges mostly apply to the non-functional properties of the communication: availability, security, and real-time [101]. Regarding radio coverage and connectivity, the availability requirement is of uppermost importance, since they are basic network services.

The *radio propagation environment,* or *environment*, is the communication medium for wireless networks. It is the place where the network operates. The *environmental dynamics* are changes of the radio attenuation properties of the environment (e.g. new obstacles, movement of obstacles, increased humidity).

The environmental dynamics is typical for industrial automation scenarios. However, there is a key difference between the traditional systems (DML, FMS) and the future RMS with respect to these dynamics. In the traditional systems, the amount of dynamics is mostly predictable during the system design. In these systems the functionality-capacity domain is fixed. This means that the variety of the production processes is known and it is possible to predict the worst-case propagation conditions at design time. The RMS works in a completely different way. The production process and the manufacturing system layout are reconfigured to meet the actual demand. This means that the variety of the production processes is not known at design time. Therefore, at a future time the worst-case propagation conditions are different from the ones at design time.

In the European project Flexware for wireless communication in industrial environments [63] one *end-user requirement* is that, “The network should be able to operate in a harsh dynamic environment with large metallic parts (machines)” (requirement R-AR002). In addition, one of the target application scenarios, *coming from an automotive supplier*, is a clear example of a reconfigurable manufacturing system (“adding/removing workstations to increase/decrease production, reconfigure and re-allocate tools for another production line”, [63], section 4.1.3). *Suppliers of industrial wireless components* report that in manufacturing scenarios the environmental conditions and influencing factors are dynamic [24][76]. The book “Wireless Networks for Industrial Automation” identifies the dynamics of the environment in industrial scenarios. They are one of the main challenges for wireless communication ([52], section 1.3.1).

All these examples clearly show that in the factory of the future the propagation environment will be dynamic. The environmental dynamics are hardly predictable at design time. But it can negatively affect the radio coverage and the connectivity of a WMN. Still the availability of these services should be guaranteed. Hence, it is required that the radio coverage and the connectivity have high availability in a dynamic propagation environment.

Other challenges and constraints of industrial wireless communications
In addition to the *high availability* and *dynamic environments*, the use of wireless communication in industrial automation environments poses additional requirements and constraints. An industrial automation factory is a relatively complex system, consisting of heterogeneous components and technologies. Some of them are primary; meaning that they perform the production process. For instance a mobile transport robot transporting goods. Others are supporting components, meaning that they support the process, but are not the main mission of the factory. The wireless network, that is used to communicate a work order from a manufacturing execution system to the mobile transport robot, is a supporting component. The main goal of a factory is the continuity of the production process. Therefore, all efforts and experiences of the operating staff are invested in supporting the primary components and the production process. It is acceptable that the operating staff also maintain the supporting components. However, it is not acceptable to require specific knowledge for every supporting component. Therefore, the wireless network should be simple to operate. Since it is a complex system, it should abstract from its complexity in the interfaces to the operating staff. An example of such abstraction is the replacement of a failed access point. Most industrial products (e.g. from Phoenix Contact, Siemens) store the access point configuration on a memory card. If an access point fails, the operator replaces it and configures it by plugging in the memory card. In this way the operator is abstracted from all IT/wireless details of the configuration (like network ID, channel, security credentials, IP configuration, etc.). In a panel discussion [130] a chief technology officer of an industrial automation company has summarized that industrial wireless communication should provide full coverage of large areas, high availability. It should not require manual site surveys and IT/wireless experienced personnel for the operation and maintenance. The manual site surveys include performing manual measurements in the whole factory. The time and effort for this is not acceptable for industrial automation.

1.3. Requirements and Constraints

In this section, we will summarize the requirements for radio coverage and connectivity. We have derived these requirements from the industrial automation scenario described in the previous section 1.2. Our goal is to develop a method satisfying the requirements. However, the developed concept is independent from the automation industry and it can be applied to other industries, if the same requirements exist. The requirements and constraints for radio coverage and connectivity in wireless mesh networks are:

- High availability

  The wireless network supports a core business process (e.g. production). The disturbance or stop of this process leads to financial loss for the organization. For this reason, high availability of the radio coverage and the connectivity is needed. Availability is readiness for correct service which is expressed by the probability that the service is correct [40, 100]. A *service is correct*, if it is performed according to its specification. The availability of the services *radio coverage* and *connectivity* should be comparable to the availability of the physical connections in wired networks.

- Dynamic propagation environment

  The operating environment has dynamic radio-attenuation properties during the life-cycle of the wireless mesh network. These dynamics are specific to the application scenario and are not fully predictable during the deployment of the wireless network. For instance, in an industrial automation scenario the dynamics are the movement of goods or machines and reconstruction of the production lines.

- Complexity abstraction

  The main focus of the organization is the business process. The wireless network is only a supporting component for this process. Therefore, from the integrator's view, the wireless network is a black box. When it is put to work, it should be simple to operate. In a case of unforeseen dynamics of the environment this black box should adapt to the change with minimum personnel involvement required and minimum effort.

- Personnel constraints

  During the deployment of the wireless network, it is acceptable to rely on experienced (e.g. external) deployment staff. The deployment staff performs the initial installation and configuration of the network for correct services. However, in the operational phase, the maintenance of the wireless network, including the radio coverage and connectivity, should be performed by the available operating staff on-site. Typically, this operating staff is not skilled in IT and wireless networking.

- Effort constraints

  Effort is the work and time, spent on the operation of the wireless network. The effort should be as low as possible.

- Long life-cycle

  The business process and the wireless network have a relatively long life-cycle (e.g. 10-20 years).

1.4. Problem Exposition

In this dissertation we consider the problem of guaranteeing availability of radio coverage and connectivity of wireless mesh networks in dynamic propagation environments. The environmental dynamics can have a negative effect on the WMN. It reduces the radio signal strength in the service area; which can lead to failure of the radio coverage. Its effect on connectivity is that some backbone links can be lost which can disconnect the backbone network. If no measures are taken, the *environmental dynamics* can lead to service failures.

A typical approach for this type of problem is adding *static redundancy* during the system design. It compensates the negative effects of the environmental dynamics on radio coverage and connectivity at runtime. However, an important question is how much redundancy? It is unfeasible to predict all changes in the environment in the considered life-cycle of the system. Even if this would be possible, adding redundancy for all likely changes, is extremely inefficient.

Our approach is to use *adaptive redundancy*. We also add a specific amount of redundancy during the design. This redundancy is sufficient to avoid service failure at the *first occurrence* of environmental dynamics. Then the redundancy is lost, but the service is still correct. Our idea is to detect this state of lost redundancy and restore the original redundancy before a service failure occurs. Similar to the RMS manufacturing paradigm which adds additional functionality-capacity *when it is needed*, our approach adds a sufficient amount of redundancy *when it is needed*. However in order to apply this approach, we need to solve at least the two challenges: *radio coverage assessment* and *base station planning*.

The *radio coverage assessment* is the monitoring of the radio coverage at runtime. This which is especially difficult in a dynamic environment. The radio coverage is initially correct and redundant but after some time and some environment changes, this might not be the case. The challenge is to assess the parts of the service area where no mobile stations are located at the moment of assessment. For these service locations, monitoring is not possible. It is required to assess them in order to guarantee the availability of the radio coverage; in the case that a mobile station moves to such a location in the next moment in time. The radio coverage assessment is challenging because it has to be done for the whole service area. Typically, it is done with manual measurements (site surveys), but in this context, the time and effort for this manual approach is not available. Thus, a new automatic method for radio coverage assessment is needed.

The second challenge is *base station planning* for restoring the redundancy of radio coverage and connectivity. When the loss of redundancy is detected, it has to be restored by the operating staff. However, this personnel has no IT/wireless expertise and can not make appropriate troubleshooting and correcting decisions. Therefore, an automatic approach is required which supports the operating staff during the restoration of the redundancy.

As we can see, it is challenging to guarantee the availability of radio coverage and connectivity under the requirements and constraints of this thesis: long system life-cycle, few effort and non-experienced personnel.

1.5. Fault-tolerance Solution Approach

The goal of this dissertation at a generic abstraction level is to guarantee availability of the *services* (radio coverage and connectivity) of a system (wireless mesh network) which is exposed to dynamic external behavior (the dynamic propagation environment). We apply the fault-tolerance approach [40, 100, 39] which is a common approach from dependable computing for solving the problem at this generic level. Our contribution is to apply established methods from the field of dependable computing for solving a problem in wireless mesh networks. Our research contributes to physical layer availability in a joined research for dependable end-to-end communication in wireless mesh networks within our working group [16, 17][71, 87, 91, 93]. The problem and the solution approach of the thesis at an earlier stage have been presented at the day of doctorate candidates (Doktorandentag) of the Computer Science faculty (University of Magdeburg) [4]. Figure 1.2 on the next page shows an overview of our solution approach.

Fault-tolerance avoids service failures in the presence of faults. *Service failure*, or simply *failure*, is the inability of a system to perform a service according to the service specification. *Error* is a part of the system state which may lead to a subsequent service failure. A *fault* is the cause for an error. The fault-tolerant system design includes *fault model definition*, *error detection* and *system recovery*. The fault model definition identifies a set of faults for which service failures do not occur. The error detection identifies errors in the system, caused by the faults. The system recovery transforms a system with errors to a system without errors. The idea is to detect errors and perform system recovery *before* the errors lead to failures. In this way, the fault-tolerance approach avoids failures, if faults from the fault model occur.

A fault in our system is the *environmental dynamics*. This is the introduction of new obstacles or movement of obstacles in the propagation environment. If no measures are taken, this fault can lead to service failures of radio coverage and connectivity.

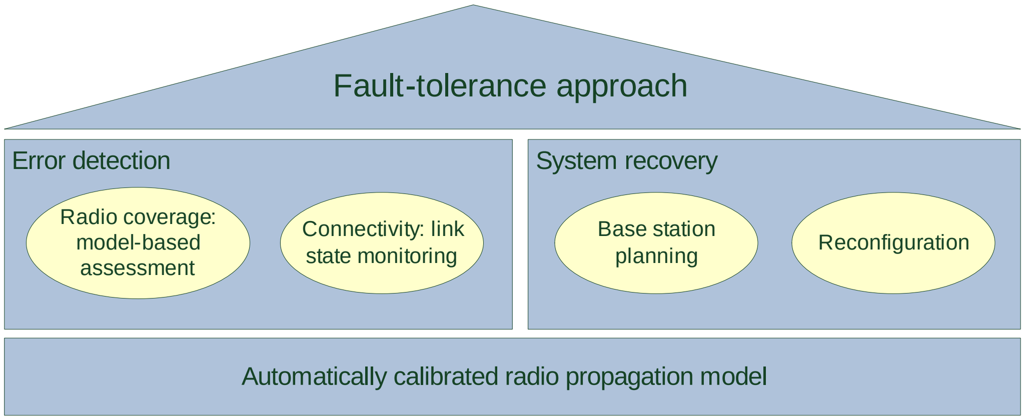


Figure 1.2.: Fault-tolerance solution approach

Our system design uses redundancy in the services for tolerating the faults. Redundancy in the radio coverage is a signal strength which is higher than the required minimum signal strength. Redundancy in the connectivity is a biconnected backbone instead of a single connected backbone. However, in our approach, the redundancy is not a static deployment-time redundancy, like in the state-of-the-art approaches. When the factory-layout changes for adapting to a new market, then the redundancy of the WMN services changes for adapting to the new propagation environment [9]. We define the loss of redundancy in the services at runtime as an error. In the error state, the services are correct. If no measures are taken, this state can lead to service failures, if another fault occurs. Our approach is to perform error detection and system recovery before the faults lead to failure. The system recovery restores the redundancy of the services.

Our approach for error detection is twofold for the radio coverage and for the connectivity. For *connectivity error detection,* we use classic biconnectivity testing algorithms based on link state information from the routing layer. *Every link state is determined by two communication endpoints* which enables us to detect connectivity errors by *monitoring* at the routing layer. However, the same approach can not be applied to *radio coverage error detection*, since a communication endpoint at every service location does not exist. Our approach is to use a *model-based assessment* for detecting radio coverage errors at the physical layer. We use a radio propagation model for assessing the radio signal strength at every service location. The classic radio propagation models are static and fixed. The innovation of our approach is that in our system the radio propagation model *automatically calibrates* to the real environment. In this way, the model detects the environmental dynamics.

Our approach for system recovery is to add new base stations to the network. The new base stations improve the radio coverage by increasing the radio signal strength at the service locations. The new base stations also improve the connectivity by adding new links to the backbone network. Our approach automatically determines the number and positions of new base stations to be installed. This is done by our base station planning algorithm [12] which uses the calibrated radio propagation model. The operating staff performs the network reconfiguration which restores the redundancy of the services.

Automatic radio model calibration is a fundamental function in our system. This function uses radio signal strength measurements from the WMN for adjusting the model parameters to the real environment. In this way, this function detects the environmental dynamics. The calibrated radio model is used for both error detection and system recovery. The error detection uses the model for automatic assessment of the radio coverage at runtime. If an error in the model occurs, then this is also an error in reality. The system recovery uses the model for predicting the effect of possible network reconfigurations on the services. If a reconfiguration in the model restores the redundancy of the service, then it will also have the same effect in reality.

For model calibration, radio signal strength measurements at known positions are required. The existing approaches use manual measurements for model calibration. We provide two approaches for automatic calibration: infrastructure-based calibration and localization-based calibration. The infrastructure-based approach uses measurements among the base stations in the network [10]. The localization-based approach uses measurements from the mobile stations. For obtaining location information from these measurements, we have developed a new network-based localization method [11].

The connectivity in wireless mesh networks needs at least two basic functions. The first one is the deployment and operation of the base stations. This function ensures that a sufficient number of base stations exist and they are located in the environment in such a way that a connected routing layer topology is possible. The second function is the multi-hop routing protocol. The routing protocol discovers the topology of the wireless mesh network at runtime and propagates it through the network.

In this dissertation we have developed methods for the first function (deployment and operation of base stations). This is in particular our base station planning algorithm [12]. For the routing protocol, we base on the long standing research and practical experience of our working group on multi-hop communication [1, 3, 2, 7, 20, 21][25, 71, 72, 87, 90, 94].

1.6. Structure of the Thesis

The rest of the thesis is structured in the following way: in section 2 we will discuss related work. In section 3 we will present our approach for fault-tolerant radio coverage and connectivity of wireless mesh networks in dynamic propagation environments. The next two sections will describe the fundamental concepts of our fault-tolerance approach. Section 4 will present our approach for automatic radio model calibration. Section 5 will define the base station planning algorithm. Section 6 will describe our implementation prototype and will provide experimental evaluation of the developed concepts. Finally, section 7 will conclude and will provide directions for future research.

2. Related Work

Firstly, we will present related work aiming at availability of the radio coverage (section 2.1). Then we will discuss related work to the basic components of our solution approach: radio model calibration and model-based assessment, localization and base station planning. Section 2.5 concludes the related work by discussing selected aspects of industrial wireless communication.

2.1. Availability of the Radio Coverage

Radio coverage as a requirement for wireless communication The availability of the service *radio coverage* is a necessary condition for reliable communication in wireless networks. The issue of reliable communication via wireless medium has been extensively investigated during the design of every wireless communication system. Since the wireless medium is unshielded, the effect of the environment on the wireless communication is specific to the environment. Different methods have been developed for increasing the reliability of the communication through the wireless medium. Most of them are at the physical layer. For instance the robust modulation methods (e.g. MIMO), frequency hopping, spread spectrum transmission, redundancy in the antennas [142], and redundancy of the transmitters [77]. At the data link layer, error correction codes and retransmissions are typical measures. These methods mostly address the time-variability of the wireless channel caused by multi-path propagation. However, all these methods require some minimum radio signal strength at the receiver which is a basic requirement for decoding the frames successfully. Providing this minimum radio signal strength is a matter of network deployment and configuration in the particular environment.

The state-of-the-art static method for providing radio coverage The state-of-the-art method for ensuring radio coverage has a static nature (e.g. [149, 29]). Figure 2.1 shows the general procedure of this method. The method ensures radio coverage during the network deployment before the network starts operation. Usually, an *expert* plans the base stations properties so that the requirements for the radio coverage are fulfilled. The expert makes this planning based on knowledge about the environment and the requirements. For this purpose, measurements in the particular environment are typically needed. Then, the base stations are installed. After the installation, a manual

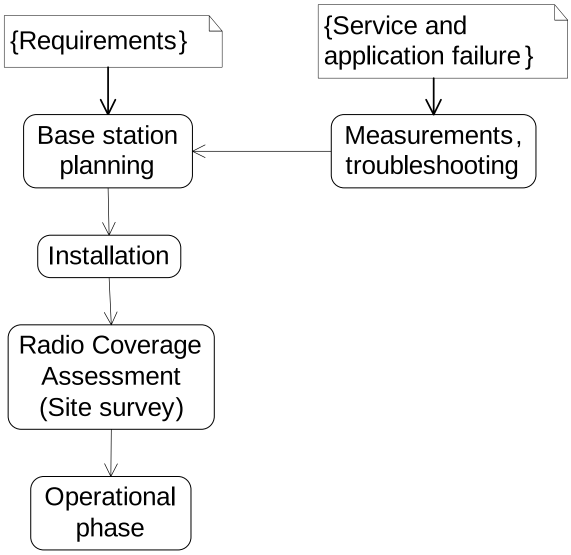


Figure 2.1.: Static deployment method for radio coverage

site survey is conducted with the purpose of proving that the requirements are satisfied. The site survey includes manual measurements of the radio signal strength on selected service locations in the whole area. If the requirements are not satisfied adjustments should be made. The adjustments are site-specific and may include removing obstacles, changing frequencies, or adding new equipment [78]. When the requirements are fulfilled, the wireless network enters the operational phase. In the operational phase, *there is no automatic function for monitoring and maintaining the radio coverage*. The only way to do this is by making a manual site survey which is expensive in terms of time and effort. The loss of radio coverage can only be detected by the mobile stations and the applications. The network connection is lost and no communication is possible. The repair of radio coverage is started when the applications report a problem of this kind. During the radio coverage repair the presence of a expert is required for troubleshooting and base station planning.

For compensating the dynamics of the environment, the static method uses static radio signal strength redundancy (called fade margin). In communication systems design the term *fade margin* (or margin) is the amount of signal strength reserve. This is the power, added to the needed minimum level for reception of the frames at the receiver. The fade margin is configured during the planning phase via adequate selection of transmitters and antennas [45]. The fade margin is used for compensating temporal variations in the environment. When the environment changes, the radio coverage eventually degrades. But if the redundancy is sufficient, the radio coverage is still correct and the applications are not affected. However, the radio coverage could have entered a critical state; meaning that further changes in the environment may lead to service failure. Since there are no automatic monitoring functions for the radio coverage, this state of lost redundancy is not detected, and remains in the system. In this state, the next change in the environment can lead to service failures.

Applications of the static method This approach has historically evolved from outdoor communication, where the weather conditions can have different effect on the propagation (e.g. satellite, telecommunication). Here, the worst case environment (e.g. highest humidity) can be estimated. Therefore, a fixed fade margin is sufficient for reliable radio coverage. This approach has been then used for indoor planning of wireless LAN; typically in office environments and buildings [29, 78]. In dedicated and flexible manufacturing systems the static approach has also been used (e.g. [38, 115],[24, 22]). If the amount of environmental dynamics can be predicted during the deployment, the static method is also feasible in an industrial scenario.

Paper [78] describes the procedures for performing a manual site survey in a WLAN for the purpose of radio coverage assessment. Before the deployment, a manual site survey is conducted for measuring the specific properties of the environment. After the deployment, another site survey is conducted in order to ensure that the radio coverage is sufficient. If not, reconfiguration should be done by removing obstacles, changing frequencies, and adding new equipment. Availability is achieved by redundancy of the components which makes two reachable base stations instead of only one. This adds some level of availability, specially in the case of equipment crash. However, a change in the environment can have the effect that both access points are not reachable. For this reason other methods are needed in the case of environmental dynamics.

The Ekahau Site Survey [29] is an advanced WLAN-planning-tool that includes modeling, site-surveying, analyzing, optimizing, simulating, troubleshooting and reporting features. However, it supports only the described static planning method. It has some diagnosing feature for analyzing the source of a problem, but the problem should be detected firstly by the applications (lack of communication); this is also not acceptable in our application scenario with high availability requirements.

The state-of-the-art static approach is used in research papers [59, 149], patents [62, 95] and commercial products [29, 78]. The static method is widely used for planning different wireless systems including point-to-point, cellular systems and in different branches including telecommunication and industrial automation. In outdoor systems fade margin is used to circumvent atmospheric-induced outages [45]. The patent [95] provides a methodology for determining the fade margin for a point-to-point wireless connection. The authors in [122] describe methods to determine optimal fade margins in cellular radio systems with the purpose of minimizing the outage probability for different types of hand-off (roaming) of the mobile stations. Paper [124] proposes a model for determining the outage probability of a mobile, moving in a cellular network, based on fade margin. However, the static method does not guarantee high availability in dynamic environments because there is no automatic network function for monitoring the radio coverage.

The need for a new method In the context of this thesis, we have high availability requirements. We have an environment which can change in unpredictable way during the network's life-cycle which is typically larger than 10-20 years. For this reason, it is hardly possible to plan sufficient static redundancy for all possible changes of the environment. They are not known at the deployment phase. Even if this would be possible, it would be extremely inefficient. Consequently, a new method is needed for guaranteeing radio coverage. When the factory-layout changes for adapting to a new market, the method should enable an easy adaption of the WMN and should guarantee high availability of the radio coverage and the connectivity.

The EU-funded research project ^{flex}WARE (Flexible Wireless Automation in Real-Time Environments) develops a communication system for factory-wide wireless real-time control [31]. The system includes a "Resource Management" module which is dedicated to providing radio coverage during the design and operational phase of the system. The concepts developed in this thesis for error detection and system recovery of the radio coverage have been adopted in the system design of ^{flex}WARE.

2.2. Radio Coverage Assessment and Model Calibration

Methods for radio coverage assessment In general there are two approaches for assessing the radio coverage which are used in infrastructure networks: measurement-based and model-based [149]. The measurement-based approach uses manual signal strength measurement on the majority of the service locations [29, 78] which contradicts our effort constraint. The model-based method performs automatic assessment based on a radio propagation model. However, the values of the model-parameters are fixed. They are typically derived from the literature (e.g. [42, 108]) and do not adapt to the dynamics of the environment. In a dynamic environment, the model should to be calibrated to the real environment which also requires manual measurements. The challenge is to perform *automatic calibration* of the model without manual measurements and without neglecting the accuracy of the assessment.

There is quite a number of radio propagation models (see [111] for a detailed survey). Most of them rely on the user to build a model manually. Some models allow us to use real measurements for parameter calibration (e.g. [83, 118]). However, this requires a manual site survey. In addition, calibration is today done only manually and in the initial phase. This does not reflect the environmental dynamics. The European initiative COST231 has developed different radio propagation models [27]. However, the issue of online model calibration and automatic detection of changes in the environment has not been addressed.

Radio channel characterization in different environments Various scientific papers report the results of radio signal measurements in different environments. Paper [103] derives the parameters of a single-slope log-normal propagation model from a set of measurements. The particularity in this case, is that the derived path loss exponent is lower than 2 which means that the radio signals propagated better than in free-space. This effect is due to the wave-guiding effect of a corridor which supports the radio propagation in a particular direction. In addition, the authors have measured the effect of movement of a small number of people along the propagation path. The people's movement had a noticeable effect on the RSS standard deviation, but not on the RSS-mean. This type of movement is part of the daily dynamics and is not considered as environmental dynamics in our case. Paper [98] reports a similar characterization of the radio channel in an industrial environment. As a summary, the radio channel has been characterized in different environments. However, these are always studies in a specific environment in which the model parameters are determined from a set of manual measurements. To the best of our knowledge, no method has been published that is able to perform channel characterization online and detect changes in the environment without manual effort.

Radio modeling approaches There is a trade-off between two types of existing radio propagation models. The deterministic models are more accurate but require high modeling effort and long execution time; while the statistical models require acceptable modeling effort and are computationally much faster, but are less accurate. The deterministic models (e.g. [117, 146]) reproduce the radio wave propagation effects (reflection, diffraction, scattering) and are relatively accurate; leading to reliable assessment. However, the computation takes relatively a long time. In a small scenario, with 3 access points, the implementation took 2 minutes, even with the optimized dominant path model [48]. The long running time is problematic for the error detection and the system recovery in large network scenarios. In addition, in order to be accurate these models require high-fidelity information about the environment (every significant object like a wall, elevator, shelf, machine, etc. has to be present). This leads to extreme effort during the input of this information but also for its maintenance as the environment changes. This contradicts the effort constraint. The statistical models (e.g. [118, 83]) are based primarily on the distance on a single path from a transmitter (T) to a receiver (R). The whole environment is described only by two parameters: the environment attenuation factor and statistical variance. These models require low effort and are fast, but they are less accurate because they assume a homogeneous environment.

The need for a new method Based on the presented related work, we conclude that a new method for radio coverage assessment is needed. It should automatically detect the environmental dynamics without the need of manual measurements. In addition, this new method should have a suitable radio modeling approach: adequate running time, little modeling effort, and also an accurate assessment.

2.3. Localization in Wireless Networks

In general, localization can be done by many different methods and technologies. The Global Positioning System (GPS), for instance, is a widely used system for satellite navigation [104]. Other approaches, for instance, use WLAN-localization, RFID tags [102, 106], ultrasound [107], Ultra Wide Band [126].

In this thesis, localization is used to obtain information from the mobile stations for the purpose of radio model calibration. For this reason, we focus only on localization methods based on WLAN. The other methods require some additional reference system (e.g. RFID readers) or additional mobile stations (e.g. GPS receivers). The advantage of using WLAN for localization is that the existing infrastructure is used as a reference system and the existing mobile stations are reused as well. However, as we will see below, this comes with some additional overhead for the initialization; at least for the radio signal strength approaches. Localization in WLAN is usually done by radio signal strength (RSS) [42, 127, 148][11] and propagation time [89, 69][23]. First, we will introduce some general notions about the localization systems which serve as a basis for the later discussion. For the introduction of these notions, we use a GPS navigation system as an example, since these systems are common.

The phases of a localization system

The operation of a localization system can be divided in the following phases (see figure 2.2):

Initialization This is the installation and the setup of the localization system. This includes a reference system and mobile stations. In a GPS navigation, for instance, the reference system consists of all satellites in the earth's orbit and the radio signals they are emitting. The mobile stations are the navigation systems.

Location estimation In this phase, the locations of the mobile stations are determined. This is done either by the reference system or by the mobile stations. The locations are determined based on signals emitted by the reference system or by the mobile stations and by using a location estimation method. In the GPS navigation system example, the mobile stations determine their positions from signals sent by the satellites. The signal contains information about the satellites' locations, the time of sending the signal and clock synchronization information. The mobile station determines the distance to four satellites from the signal propagation time. The position is determined by trilateration from the distances and the satellites' locations [104].

Phases of a generic localization system	Example: GPS navigation	Standard RSS -based localization	Our localization approach
Initialization	Get a dedicated navigation device	Use the existing network, Static and manually generated training data	Use the existing network, Adaptive and automatically generated training data
Location estimation	Trilateration. Distances to satellites, determined from signal propagation time	Nearest neighbour search (deterministic and probabilistic)	—
Estimation improvement	Based on Kalman filter, vehicle speed, roads' coordinates	Kalman filter	Kalman smoothing (forward and backward filter)
Interpretation of location information	Give driving directions	—	Use localization results for radio model calibration

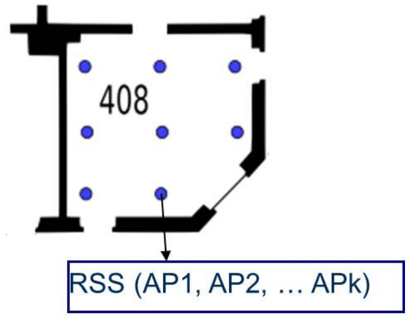
Figure 2.2.: Our localization approach is innovative in the phases *Initialization*, *Estimation improvement* and *Interpretation*

Estimation improvement In this phase, the location estimation is improved. Typically the location estimation has some inaccuracies caused by measurement errors. Usually, in this phase noise filters are used together with some application-specific information. In the GPS navigation system example Kalman filters are used to filter out the noisy measurements. Additionally, information on roads' coordinates and the vehicle's speed is used to determine the most probable location.

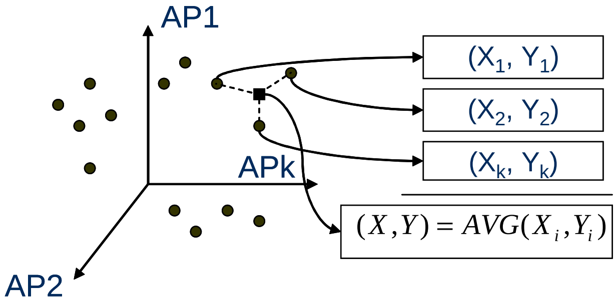
Interpretation During the interpretation phase the location estimation is used by the application. In the above example the GPS navigation system gives driving directions to the driver based on the location estimate, velocity estimate, road-maps, and driving destinations.

RSS-based systems

The localization methods based on radio signal strength are mapped to the generic localization system (figure 2.2) in the following way. For initialization and location estimation, the RSS-based systems use a machine learning approach (figure 2.3). During the initialization phase, training data is collected or generated. The training data is a mapping between the positions of a mobile station at different training locations and the received RSS from (or at) the base stations. Different approaches are used for the initialization: e.g. manual walk-around [42, 127, 148, 28, 26], model-based [42, 57], or interpolation [70, 110]. During the location estimation phase, the position is determined by comparing the actual RSS measurements to entries in the training data. Different



A) Initialization (training) phase



B) Location estimation phase

Figure 2.3.: Location estimation in existing methods based on radio signal strength

approaches are used in the location estimation phase. The simplest is the nearest neighbor search in the signal strength space[42]. It is a k-dimensional space where every dimension is the radio signal strength of a given base station (AP). In this example, the position is determined by averaging the training locations of the three nearest neighbors in signal strength space. Alternatively, various probabilistic search methods have been developed which use Bayesian probability [148, 127, 28]. The initialization methods can be divided into manual and automatic methods.

Manual initialization The manual group (e.g. [42, 148, 28, 26]) are training-based approaches. During the training phase, environment-specific knowledge about the receivable access points (AP) and their signal strength is collected by manual measurements (walk-around). However, when the environment changes, the measurements have to be repeated, or the localization accuracy will eventually decrease. This is a disadvantage for scalability in industrial plants. The innovation of our approach is that it generates the training data automatically based on the calibrated radio propagation model.

Some research works used linear interpolation among (fewer) manually measured training locations for decreasing the training effort; for instance [70] and the isolines approach [110, 67]. In contrast, our method completely eliminates the need for manual training.

Several projects exist for providing localization services for public communities for client-based localization (e.g. PlaceLab [75], MagicMap [51]). Their objective is to support different technologies like WLAN, Zigbee, RFID, Bluetooth, GSM-signals and to be accessible to everyone. They maintain a publicly-available database of hotspot-beacon information. Users are free to use and update this through reference measurements in the areas. Due to the requirement for minimum need of reference measurements, these methods use another approach for location estimation. Distances between the mobile nodes and fixed nodes are estimated from RSS. A graph-based approach is used to locate the mobiles at positions minimizing the graph-tension. However, the environment is not modeled as a dynamic factor (which is acceptable for self-localization). Therefore, these systems require manual measurements to react to changes in the infrastructure or environment. In contrast, our approach detects the dynamics of the environment. Additionally, it uses infrastructure-based localization meaning tighter control and higher availability for industrial applications.

Automatic initialization Approaches have been developed and evaluated to generate the training data from a propagation model. The authors in [42] use a single-path model and calibrate it with manual measurements. Our method is innovative by calibrating the model online with automatic measurements and allowing a faster reaction to changes in the environment.

The papers [43, 44, 57] propose, almost simultaneously in time, a method for initialization of the localization which is similar to our initialization approach [11]. The authors use RSS measurements among fixed measurement devices for calibrating a radio propagation model to the environment. The used model is slightly different in that it models the walls. Therefore the calibration procedure includes some additional parameters. The evaluations are in office environments. The evaluation results are similar to our results, reported in section 6.4.2. The automatic training method achieves comparable location estimation accuracy, but saves the time and effort for the initialization.

Still, to the best of our knowledge, our approach is the first to use the localization results for model calibration. In this way, our innovation is to use information from the mobile stations for detecting the environmental dynamics. In addition our evaluation is in different (office and industrial) environments.

The propagation time systems

measure the time of the radio waves propagation via the air. Since the speed of the propagation of radio waves is known, it is possible to determine the distance and the relative location of objects in space. The two most common approaches are Time of Arrival (ToA) and Time Difference of Arrival (TDoA). The ToA methods measure the propagation time (and derive distance) to four base stations and determine the location in 3-D space via trilateration. The TDoA methods measure the difference of arrival of one radio wave sent by a mobile station, and received by four base stations.

However, for achieving the needed localization accuracy, the propagation time methods require a time synchronization among the base stations with a nanosecond precision. For this high precision, a *wired backbone* among the base stations is necessary [65, 89, 116]. The Epsilon-WiFi research project has developed a system for highly precise hardware-based clock synchronization and time-stamping [66] and TDoA based localization [65, 66, 89, 88, 116]. One of the main challenges has been to detect the first occurrence of a frame at the AP due to multi-path. Alternative approaches [69] measure the time in software; but achieve a higher inaccuracy (distance measurement inaccuracy of 5 to 25 meters).

Since, in our context, we consider wireless mesh networks, the wired backbone is not available. Our experience in the software-based time synchronization in mesh networks [92, 93] shows that a microsecond precision is possible; which is insufficient for propagation time based localization. For this reason our approach uses a RSS-based localization.

Estimation improvement

Kalman filtering is a widely used approach for improving the location estimation in localization systems based on different technologies (e.g. [53, 116]). The goal of the improvement in most systems is to make the last (most actual) location estimate the most accurate. For this reason Kalman filter has been used. In our situation, we are interested in improving the location estimate for a whole observation time sequence. Every location estimate is used for model calibration. For this reason, we use Kalman smoothing; which is a Kalman filtering in forward and backward direction. We experimentally proved that in different environments, Kalman smoothing achieves a better estimation improvement than Kalman filtering (section 6.4.3).

An additional issue is the setting of the noise parameters of the Kalman filter. The choice of these parameters can have a significant effect on the results [116]. Still, there were no guides as to now to determine the values of the noise parameters for WLAN-based localization. We have defined a simple procedure for determining the noise parameters (section 4.4.5) which achieved a significant improvement (section 6.4.3).

The need for a new method

WLAN-based and RSS-based localization are extensively investigated topics in the last years. Still, to the best of our knowledge, they have not been used for an automatic model calibration and detection of the environmental dynamics. For this reason a new method is needed which also requires some necessary adjustments of the localization methods; in particular the phases: initialization, estimation improvement, and interpretation.

2.4. Connectivity and Base Station Planning

In this section we focus on the deployment and operation of the base stations which is an essential function for connectivity. For the routing protocol and the topology discovery we base on the research within our working group (e.g. [71, 94, 87]).

Industrial automation networks have usually been isolated, single-cell networks or classic infrastructure networks with multiple cells. This means that base station planning is required only for the 'last mile', i.e. the connection between a base station and a mobile station, e.g. [54]. In the case of multi-hop wireless mesh networks, the planning of the backbone network is a new research aspect that needs to be considered. Research on radio network planning consider network throughput as a main planning goal, e.g. [50]. However, the most common requirement of industrial networks is availability. With the introduction of technologies for multi-hop communication in industrial environments (e.g. Zigbee, Wireless HART), the base station planning problem gains importance. Paper [109], for instance, presents the challenges for developing a planning tool for industrial wireless sensor networks. However, to the best of our knowledge, no systematic approach exists for planning multi-hop wireless networks with respect to fault-tolerance requirements of industrial automation networks.

The existing algorithms for the base station planning in wireless mesh networks [36, 120] have a different goal. It is to design a mesh network with a minimum number of base stations such that the end-to-end throughput requirements of application flows are fulfilled. These requirements are typical for Internet access in areas with no alternative high-speed wired connection. The approach is to transform the planning problem into a linear optimization problem which is a combination of a set covering problem and a network flow problem. As a result, the backbone is a connected graph, but with no fault-tolerance. Another disadvantage is the intractability of the proposed approaches. For some inputs, the algorithm takes too much time for the result to be useful. This is because the underlying linear optimization problem is a binary integer problem which is well known for its NP-completeness. Paper [120] addresses this issue by a decomposition method, but the algorithm still runs about 22 hours for a network with 58 nodes. This is acceptable for the mentioned scenarios, but for network reconfiguration in automation scenarios a faster algorithm is required. Extending these algorithms to fault-tolerance would mean an additional increase in the complexity. Paper [84] addresses the problem of fault-tolerant deployments of wireless ad-hoc networks. The authors present a method for determining the probability that a backbone network graph is k-connected, based on the transmission range. However, a basic assumption of the method is that the network can be modeled as a union disk graph where all nodes within a given transmission range are perfectly reachable and all nodes outside this range are not reachable at all. It has been shown that this network model does not comply with real networks [82]. Paper [135] considers the problem of coverage control in wireless sensor networks, including various aspects like activating/deactivating of the nodes, finding the coverage characteristics of a given network, and sensor node deployment. However, all considerations include only the aspect of last mile coverage, i.e. the sensing function of the nodes. They do not consider the problem of the backbone connectivity for communicating the sensed data to a central instance.

Our approach is to extend the existing methods from infrastructure network planning to planning multi-hop wireless mesh networks with fault-tolerance aspects. Other papers about fault-tolerance in wireless multi-hop networks can benefit from our approach for generating a fault-tolerant topology. Papers considering fault-tolerant routing, for instance [79, 85, 41, 55], have a prerequisite of biconnected backbone network, but do not address the base station planning problem. The base station planning problem has been little addressed so far because in most mobile ad-hoc and sensor network scenarios the number and position of the nodes are considered uncontrolled or hardly controlled. However, in automation scenarios the networks are typically planned to provide service in some predefined geographical area (e.g. production hall). This requires careful base station planning for ensuring high availability of the radio coverage.

The topology control problem is to configure a given an instance of a multi-hop network such that it is connected and a quality of service property is fulfilled. Depending on the configured parameter, these methods adjust the transmission power [49] or the time of activity and sleeping periods of the nodes [46]. Paper [49] presents an algorithm for distributed adjustment of the transmission powers of the nodes with the purpose of minimizing the interference and keeping the network topology connected with a high probability. Paper [46] presents a distributed protocol for topology management which determines the active and sleeping periods for the nodes in such a way that the network is connected, the energy consumption is minimized, and the data is delivered with real-time guarantees. Paper [128] considers the issue of data forwarding in industrial wireless sensor networks and the integration in a wired backbone. It proposes a chain-based communication protocol for real-time communication over multiple hops. It is common for all topology control protocols that they operate on some existing instance of a multi-hop network. For achieving the required quality of service property, these protocols require some topological properties of the network (like connectivity or k-connectivity). The difference is that our base station planning algorithm plans a given network to be deployed with the desired topological properties. In this way, our algorithm can be used in the first phase of planning the topological properties of the network. In a second phase a topology control algorithm can be used to additionally adjust the transmission powers or active/sleep times of the nodes for achieving the required QoS property.

2.5. Industrial Wireless Communication

The use of wireless networks in industrial automation scenarios has lots of benefits but poses various challenges to the non-functional properties of the communication; including the availability, security and real-time [101, 143]. A review article from the transactions on industrial informatics [143] gives an overview of the current trends and research direction in industrial wireless communication. The author recognizes that engineering and network planning including runtime fault monitoring is an important research area for industrial wireless networking. The radio coverage and the connectivity are one of the main prerequisites for the availability of the communication.

Security is an important topic, since wireless communication eases the access to the industrial networks which have been usually isolated only by physical means. Important for security is to apply a risk-based approach for selection of controls and to consider security during the whole life-cycle of the manufacturing system [5, 6]. Within the research project Flexware, we have developed methods for supporting the operating company during the risk analysis [14, 15]. Following the risk analysis, it is often the case that the available security controls do not satisfy the particular requirements; then the development of new security controls is needed. Paper [23], for instance, proposes a new localization-based access control mechanism. When security has to be implemented in industrial embedded systems and fieldbuses, new solutions are needed to address different challenges, for instance the trade-off between system performance and protection level [132, 133].

Real-time communication is important for the control of automation devices. A prerequisite for real-time communication is the availability of the communication. On this basis, the real-time guarantees are achieved by admission control and scheduling of the application flows. See papers [1][73] for an admission control method for mesh networks. The scheduling algorithm determines a transmission schedule for the flows. The dissertation [114] has developed a middleware for timely predictable group communication and task execution in a single-cell network; based on methods for dynamic network and task scheduling. The paper [129] proposes a scheduling algorithm for multi-cell networks and different flow types (periodic, aperiodic). The medium access protocol is another essential element for real-time communication. The IsoMAC protocol, developed in the Flexware project, is a TDMA based protocol for real-time communication [64]. It provides isochronous medium access which is specially important for communication with fieldbus automation devices. If the network consists of multiple cells, it has to be considered that the mobile stations change their base station associations. In mesh networks only rerouting is needed, since no roaming occurs. Still, methods for fast link failure detection are needed to initiate the rerouting on time [87]. In infrastructure networks the roaming needs to be fast. The time for reconfiguration of the forwarding on the data link layer has to be considered as well. Papers [134, 145] propose methods for fast roaming in industrial infrastructure wireless networks. In complex automation systems with multiple co-located wireless technologies the coexistence has to be considered. The coexistence is ensured by organizational methods (e.g. the VDI guidelines for coexistence [35]) and by specific evaluation of the considered technologies in a particular case (e.g. [47]).

3. Fault-tolerant Radio Coverage and Connectivity

This section presents our approach for fault-tolerant radio coverage and connectivity of wireless mesh networks in dynamic propagation environments. This approach has been published in [9].

3.1. Fault-tolerance Approach

We consider the goal of this dissertation at a general abstraction level. It is to guarantee availability of the services (radio coverage and connectivity) of a system (wireless mesh network) which is exposed to dynamic external behavior (the dynamic propagation environment). The environmental dynamics is an external factor to the wireless network. It results from the changing surroundings of the wireless network (see section 1).

For this general type of problem, a well-known method exists in the field of dependable computing. This is the *fault-tolerance* approach [40, 100, 39]. Fault-tolerance avoids service failures in the presence of faults. *Service failure*, or *failure*, is the inability of a system to perform a service according to the service specification. *Error* is a part of the system state which may lead to a subsequent service failure. A *fault* is the cause for an error. The fault-tolerant system design includes *fault model definition*, *error detection* and *system recovery*. The fault model definition identifies a set of faults, for which service failures do not occur. The error detection identifies errors in the system, caused by the faults. The system recovery transforms a system with errors to a system without errors. The idea is to detect errors and perform system recovery *before* the errors lead to failures. In this way, the fault-tolerance approach avoids failures if faults from the fault model occur. In this dissertation we apply the fault-tolerance approach for guaranteeing availability of radio coverage and connectivity of wireless mesh networks in dynamic propagation environments.

Fault model definition

A fault in our system is the *environmental dynamics.* Environmental dynamics are changes of the radio attenuation properties of the environment (e.g. new obstacles, movement of obstacles, increased humidity). The *attenuation* describes the ability of the radio propagation environment to absorb and weaken the radio waves. An increased attenuation has a negative effect on radio coverage and connectivity. Regarding radio coverage, it reduces the radio signal strength at the service locations. This can lead to the fact that some service locations are not covered. The effect on connectivity is that some backbone links can be lost. This can disconnect the backbone network. If no measures are taken, the fault *environmental dynamics* can lead to service failures. A fault is the event of environmental dynamics which decreases the $ARSS$ (Average Radio Signal Strength) up to a user-specified amount $\Delta ARSS$.

Fault-tolerant system design

Our system design uses redundancy for tolerating the faults. Figure 3.1 shows the state machine of our fault-tolerant system. The figure shows the system states, their attributes and their entry actions. The initial state is the normal state. In addition to the *correct service*, the normal system state contains *redundancy* for compensating the faults at run-time. In this normal state the system performs *concurrent error detection*, meaning that the error detection takes place during the normal service delivery. In the *error* state the redundancy is lost due to a fault, but the service is correct because the initial redundancy has compensated the negative effects of the fault. In this state, the system performs system recovery. The system recovery restores the initial redundancy. In the following sections we will specify how we applied this concept to the services *radio coverage* and to *connectivity*. For each service we will define the correct service specification, the redundancy and the error. A failure for both services occurs when the service consumer (a mobile station) tries to use the service and the service is not correct. Our fault-tolerant system design avoids the failures.

3.1.1. Radio Coverage

Correct service

Radio coverage is correct if every service is covered by at least one base station with a radio signal strength of at least $ARSS_{Min}$.

Redundancy

In order to ensure correct radio coverage in case of faults, the normal system state uses radio signal strength redundancy. This means that every service location is covered by at least one base station with a radio signal strength of at least $ARSS_{RED}$. $ARSS_{RED}$ is the value of the redundant radio signal strength needed for compensating the environmental dynamics during the error detection and system recovery ($ARSS_{RED} = ARSS_{Min} + \Delta ARSS$).

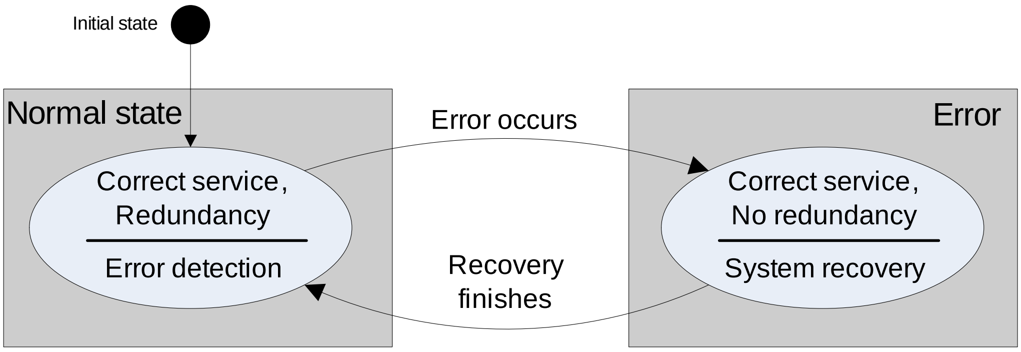


Figure 3.1.: The states of our fault-tolerant system

Error

In the error state, the radio coverage is not as good as the radio coverage in the normal state, but the radio coverage is still correct. An error exists, if at some service location the $ARSS$ is less than the redundancy value, but it exceeds the minimum threshold for correct coverage: $ARSS_{RED} > ARSS \geq ARSS_{Min}$.

3.1.2. Connectivity

Correct service

Connectivity is correct if the backbone graph is connected.

Redundancy

In order to ensure correct connectivity in case of faults, the backbone graph is *biconnected* (2-connected). A graph is biconnected if any two vertices can be joined by two independent paths [58]. This backbone redundancy compensates for the loss of a backbone link as a result of a fault.

Error

In the error state, the backbone graph is not biconnected, but it is connected. The loss of biconnectivity can be caused by environmental dynamics leading to link loss. The loss of a link is not necessarily a connectivity error. It is an error only if it leads to loss of the biconnectivity.

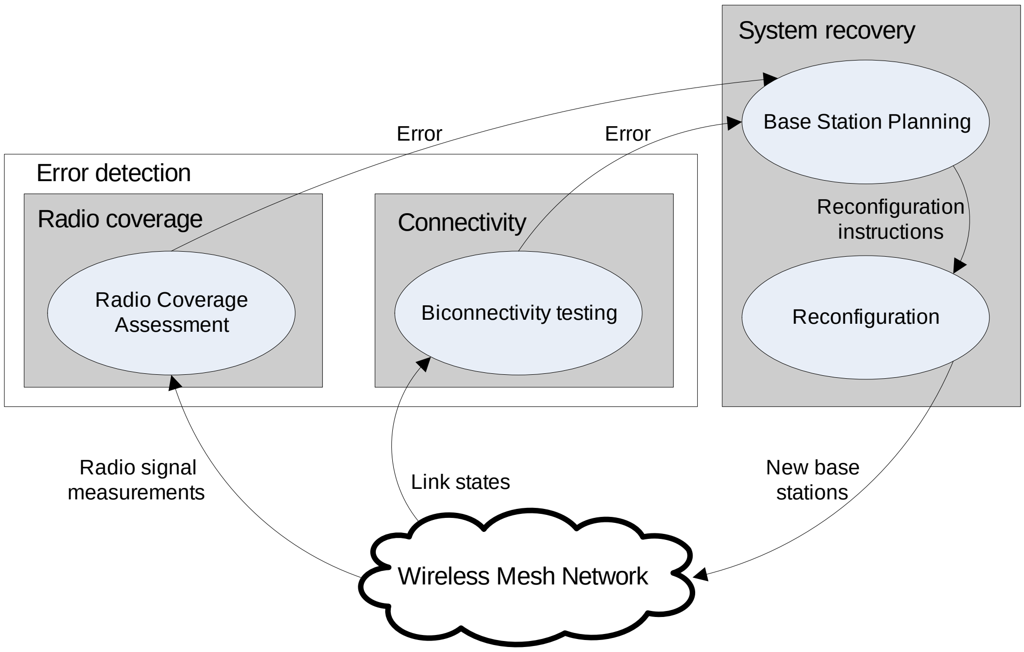


Figure 3.2.: The error detection and system recovery of our fault-tolerant system

3.2. Error Detection

When faults occur and lead to errors, the errors have to be automatically detected by the system. Since we are considering two services, radio coverage and connectivity, we need methods for detecting radio coverage errors and connectivity errors. Figure 3.2 shows our methods for error detection and their integration in our fault-tolerant system design.

Connectivity error detection

For detecting connectivity errors we use a monitoring at the routing layer and a classic biconnectivity testing algorithm from graph theory [58, 61]. This algorithm uses information about the backbone graph and determines whether it is biconnected or not. If the graph is not biconnected, then there is an error. The required information for biconnectivity testing are the edges (links) among the vertices (base stations) of the graph. In our scenario, this information is globally available at the management appliance. As a part of the routing protocol, the base stations monitor the backbone link states by exchanging control messages with other base stations [2]. The state of every link is determined by *two communication endpoints* (base stations). One of them sends control messages and the other one determines the link state based on a statistic on the received messages. The link state information is periodically updated and communicated, so the management appliance has an actual global view of the backbone network. Based on this global view, the management appliance performs biconnectivity testing. The fact that *every link state is determined by two communication endpoints* enables us to detect connectivity errors by *monitoring* at the routing layer. If the backbone link state information is not available globally, distributed biconnectivity testing algorithms can be used (e.g. [99]).

Radio coverage error detection

The information required for radio coverage error detection is the radio signal strength *at every service location*. However, a communication endpoint at every service location does not exist. Therefore, radio coverage errors can not be detected by monitoring, as with the connectivity errors. Nevertheless, a method for detecting these errors is needed because the environmental dynamics affect the radio coverage. The radio coverage should be guaranteed for every service location *before* a mobile station moves to those locations.

Our approach is to use a model-based assessment for detecting radio coverage errors at the physical layer. We use a radio propagation model for assessing the radio signal strength at every service location. This model has a tight relation to the propagation environment. We use measurements from the wireless network for calibrating the model to the reality.

In the state-of-the art assessment approaches the radio propagation models are static; meaning that they do not reflect the dynamics of the environment. The innovation of our approach is that the radio propagation model *automatically calibrates* to the real environment. *Radio model calibration* is the process of adjusting the model-parameters in such a way that the model reflects better a set of measurements from the actual propagation environment. *Radio coverage assessment* is the model-based estimation of the radio signal strength for the purpose of error detection. Our method for radio model calibration is defined in section 4.

3.3. System Recovery

The system recovery transforms a system with errors to a system without errors. In our approach we use the same mechanism for recovery from radio coverage errors and for recovery from connectivity errors. This mechanism adds new base stations to the network. The new base stations improve the radio coverage by increasing the radio signal strength at the service locations. The new base stations also improve the connectivity by adding new links to the backbone network. Given a wireless mesh network with radio coverage and/or connectivity errors we have to decide how many base stations there is to install and and where to install them in order to correct the errors. For this purpose, we have developed an automatic base station planning algorithm [12]. Section 5 describes this algorithm.

The error recovery includes automatic base station planning and manual reconfiguration (see figure 3.2). The management appliance runs the base station planning algorithm and gives instructions to the operating staff for the reconfiguration. The operating staff performs the reconfiguration which restores the redundancy of the services.

3.4. Concept Analysis

Availability in dynamic environments The presented fault-tolerance concept requires an analysis with respect to the guaranteed availability. There are two classes of faults. The first class of faults are the faults which are defined in the fault model. When these faults occur, our fault-tolerant system design avoids failures and guarantees availability of the services. The second class of faults are faults that are not defined in the fault model. These are for instance, *burst faults* (a fault which occurs before the system recovery has been completed) or faults, for which the redundancy is not able to compensate. When these faults occur the availability can not be guaranteed and service failures can occur. In these cases, our approach increases the availability of the services by predicting the failures and reducing the repair time.

The proposed methods used for error detection can be used for predicting failures as well. The radio coverage assessment can detect that a service location is not covered. Such situation can lead to radio coverage failure if a mobile station moves to the service location and tries to use the service. The connectivity testing algorithm detects the case when the backbone graph is not connected. This situation can lead to a connectivity failure if some station tries to communicate to the missing part of the network.

The repair time is the time needed to restore the correctness of a failed service. The repair time is reduced because the method for service recovery can be used for service repair as well. The base station planning algorithm takes a network configuration and the calibrated radio propagation model as input and returns the required reconfiguration instructions to bring the services to a normal state. The initial network configuration can contain errors, failures, or can be empty. For this reason, the algorithm can be used for both service recovery and for service repair.

Complexity abstraction, personnel and effort constraints The proposed approach performs automatic error detection which means that no effort is required. In a case of an error, the system automatically proposes a way for recovery which can be implemented by personnel without specific IT/wireless skills. The whole complexity of the error detection and system recovery is hidden in the WMN. When the environment changes, the WMN automatically proposes a reconfiguration procedure which leads to high availability of radio coverage and connectivity.

Next sections The next sections focus on the fundamental components of the presented fault-tolerance concept. These are the automatic radio model calibration used for error detection and system recovery (section 4) and the automatic base station planning algorithm used for system recovery (section 5).

4. Automatic Radio Model Calibration

In this section, we will describe our innovative method for automatic radio model calibration. Firstly, we will provide an overview of the approach and define some basic definitions in section 4.1. Then, we will describe our radio modeling approach (section 4.2), and the mathematical procedure for model calibration (section 4.3). In section 4.4 we will present our location-based approach for obtaining measurements for the model calibration in an automatic way. Finally, we will conclude this section with an analysis of the developed method in section 4.5.

4.1. Overview of the Approach

The innovation of our approach is that the radio propagation model *automatically calibrates* to the dynamic environment. *Automatic radio model calibration* is the process of adjusting the model-parameters in such a way that the model reflects a set of measurements from the actual propagation environment. For radio model calibration we need a radio modeling approach, a measurement approach, and a parameter calculation method. The *radio modeling approach* specifies the used radio propagation model. The radio propagation model is a mathematical approximation of the propagation of the radio waves through the environment. The *measurement approach* specifies how to obtain radio signal strength measurements for model calibration. The *parameter calculation method* specifies the automatic way of computing parameter values that minimize the difference between the measurements and the respective model predictions. Our idea is to perform *automatic radio model calibration*. Automatic means that the measurements and the parameter calculation are performed at runtime in an automatic way. Figure 4.1 shows the components and their interactions for automatic radio model calibration.

Our radio modeling approach is to use a statistical model in an innovative way which makes the model accurate enough and preserves its fast computation and low modeling effort. Our innovation allows the user to specify multiple environment types instead of only one. This increases the model accuracy while keeping the modeling simple. In order to guarantee a reliable assessment, our method calibrates the model and uses the model's outcome in a pessimistic way, based on information from the calibration.

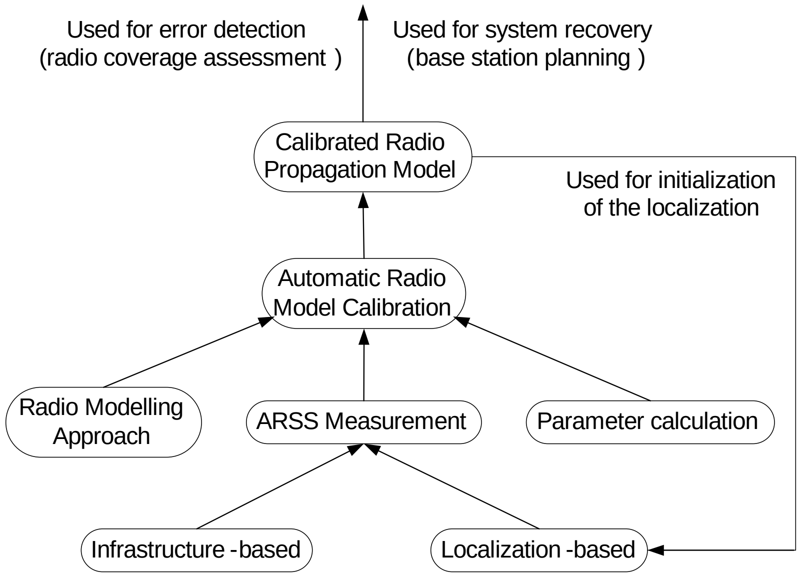


Figure 4.1.: Overview of the components and interactions in automatic radio model calibration

Our measurement approach is to measure the radio signal strength from the ongoing communication in a wireless mesh network. We present two measurement approaches: infrastructure-based measurement and localization-based measurement. We use the name of the measurement approach to specify the calibration, the assessment and the error detection respectively. For instance, localization-based error detection means that localization-based measurements have been used for model calibration and then the model has been used for error detection. Figure 4.2 shows this notion.

The infrastructure-based measurement uses the ongoing control messages among the base stations. The base stations periodically exchange control messages for maintaining the topology of the backbone which is part of the routing protocol. We measure the radio signal strength (RSS) at the base stations by using a wireless device in monitoring mode. The idea of infrastructure-based measurement is that changes in the environment have a noticeable effect on the measured RSS among the base stations. Since the positions of the base stations are known, these measurements are used for calibration of the radio propagation model.

Localization-based measurements When the base stations are not located within the service area, the infrastructure-based measurements might not detect the environmental dynamics. This can happen, for instance, if the base stations are mounted on the ceiling, the mobile stations are on the ground, and the obstacles arise from

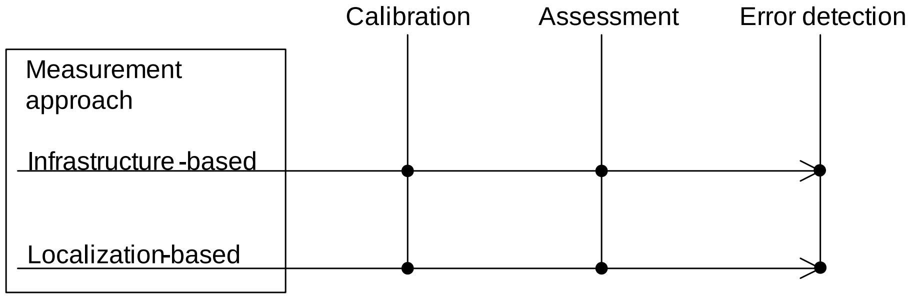


Figure 4.2.: The type of signal strength measurement specifies the type of calibration, assessment and error detection

the ground and do not reach the ceiling. In such situation it is possible that the environmental dynamics affect the communication between the mobile stations and the base stations, but does not affect the inter-BS communication. In these cases, our method uses measurements from the mobile stations. The base stations measure the RSS of messages sent by the mobile stations. Since the mobile stations also participate in the routing protocol, they periodically send messages. The RSS information from the mobile stations is collected at the management appliance in measurement time sequences. A measurement time sequence is an array containing measured RSS from a mobile station. For every time instant, the sequence contains RSS for messages, sent by the mobile station, and measured by the base stations. The measurement sequences can be collected without any effort and our idea is to use them for model calibration.

However, the problem is that the measurement sequences do not contain location information which is needed for model calibration. For this purpose we have developed a new WLAN-based localization method (see section 4.4 for details). This method performs localization in an automatic way, i.e. it does not require manual training as existing methods do. For this purpose the localization method uses the calibrated radio propagation model (see section 4.5 for a discussion). In addition our localization method is specifically tailored for the purpose of model calibration. It reduces the inherent localization inaccuracy and to some extent it even uses the remaining inaccuracy for extracting useful information from the measurement time sequences.

Our parameter calculation approach minimizes the difference between measurements and model predictions in a least squares sense. We use parameter bounds for keeping the model parameters in a realistic range. Our parameter calculation approach preserves the "no coverage" situations from the real environment in the model. The point is to not only use the measurements as in the classic methods but to use in addition the lack of a measurement. For example, when a base station is far from another, it will not receive any messages from it. This notion additionally increases the quality of the assessment by reducing the over-estimations of the radio coverage. We applied this idea by using linear least squares optimization with inequality constraints. Furthermore, our new calibration method supports multiple environment types according to the used radio model. We have addressed the problems of radio model calibration in [10].

4.2. Radio Propagation Model

4.2.1. Radio Modeling Approach

The trade-off in the existing radio propagation models is between the higher accuracy of the deterministic models and the acceptable modeling effort and fast execution of the statistical models (see section 2.2 for details). Our radio modeling approach is to use a statistical model in an innovative way which makes it accurate enough while preserving its fast computation and low modeling effort. Our innovation allows the user to specify multiple environment types instead of only one. This increases the model's accuracy and keeps the modeling simple. In order to guarantee a reliable assessment, we calibrate the model and use the model's outcome in a pessimistic way, based on information from the calibration. We use the probabilistic outcome of the model in such a way that it is very unlikely that the real radio signal strength is less than the estimated signal strength. In the majority of the cases the real signal strength is equal or higher than the estimation. In this way, the quality of the assessment is increased because underestimation is better than overestimation. A side effect is that the user might install more base stations as needed. This is acceptable for the following reasons. Firstly, the slightly increased cost for the equipment is not problematic, because considering the importance of the business processes, this is an acceptable price. Secondly, the increased density of the mesh points is not problematic because this does not significantly increase the medium utilization. In our research on routing and medium reservation, we have shown that the medium utilization depends mostly on the number of hops along the path and not on the base stations' density [1, 3, 2]. Since the routing algorithm selects the shortest path, the redundant mesh nodes do not consume significant network resources. They remain as a fallback solution in the case of faults. Some works even utilize the inherent redundancy of mesh points for increasing the reliability of the transmissions[144]. Last but not least, our fault-tolerance approach benefits from the redundancy for handling the faults.

Our modeling approach uses the log-distance path loss model. In the next section, we will describe this model and then we will define our application of this model for different environment types. Then, we will define how this model is used for error detection and system recovery.

4.2.2. Log-distance Path Loss Shadowing Model

The log-distance path loss model with shadowing [108] is the most commonly used statistical radio propagation model for indoor environments. It estimates the average radio signal strength at a given distance d from the transmitter, by using the following equation:

$$P(d) = P(d_0) - 10n\log_{10}(\frac{d}{d_0}) + X_\sigma \tag{4.1}$$

$P(d)$ is the average radio signal strength at distance d. $P(d_0)$ is the reference radio signal strength at a reference distance d_0. Typically d_0 is 1 meter and $P(d_0)$ is obtained via measurements. $P(d_0)$ is valid for all transmitters and receivers of the same type and contains the effects of the transmission power of the transmitter and the antenna gains of the transmitter and the receiver. We define one reference transmitter type and and one reference receiver type and determine $P(d_0)$ for this configuration. All other combinations of T-R types are mapped to the generic type by adding a constant factor from the transmission power and antenna gains. This factor accounts for the gain difference of a given T-R configuration to the gain of the reference T-R configuration. $P(d_0)$ is determined only once, since it does not change over time.

n is the path loss exponent. This parameter determines the rate of the signal strength decrease with distance. n is the main parameter, that models the attenuation of the environment. The shadowing factor X_σ is a normally distributed random variable with a mean of zero and a standard deviation σ. X_σ is a statistical way to model the differences in the average signal strength which occur over a large number of T-R separations with the same distance but with different obstacles along the path. This variation of the average signal strength is called shadowing. In this way the average radio signal strength at a specific service location is normally distributed about a distance-dependent mean. The parameters path loss exponent n and standard deviation σ are environmentally specific and are typically determined from manual measurements.

However, this model has some disadvantages, with respect to our context, coming from the fact that it models the distance-dependent attenuation of the whole environment with only one parameter n. Firstly, in our scenario different types of environments exist. Secondly, with one parameter it is hardly possible to detect and account for a change in the environment which is local, meaning that it occurs only in one part of the service area.

4.2.3. Modeling Multiple Environment Types

Therefore, in this thesis we use the log-distance path loss model in a specific way that supports different environment types. The basic idea is that the whole service area has a general environment type and there exist subareas with some specific environment type (see figure 4.3). Every environment type is specified by the parameters path loss exponent

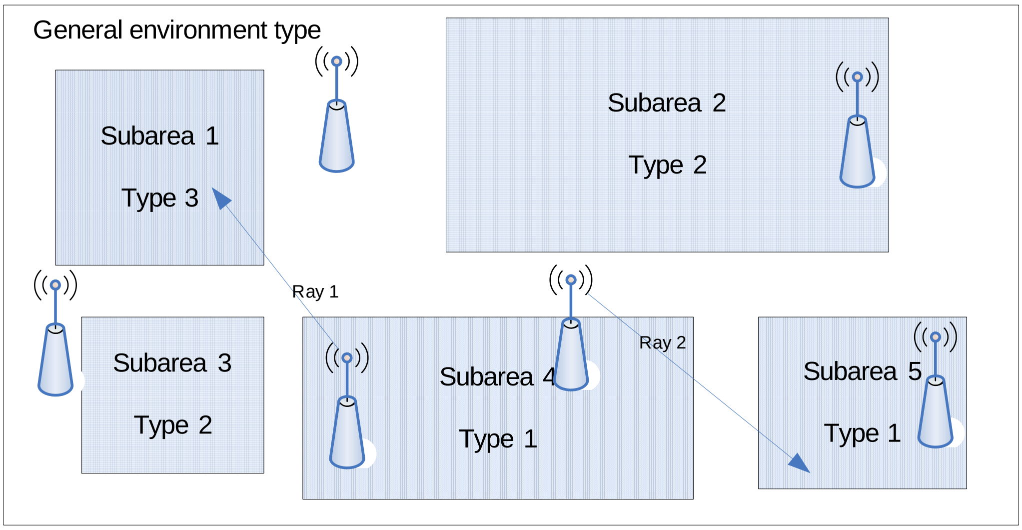


Figure 4.3.: We use the log-distance radio propagation model in a way that allows us to specify multiple environment types

and standard deviation - as the original path loss model. If at some service location a specific environment type is defined, it overrides the general environment type. It is not intended that the subareas are used to model single obstacles. Instead, they are used to identify some areas that are relatively large and have different attenuation properties (e.g. halls with machines, halls with racks, buildings with concrete walls, buildings with brick walls, etc). In this way, the user can model the environment with a manageable effort. The coordinates of the subareas and the environment type association are identified by the user. The user can support the radio coverage assessment by identifying subareas which are expected to change. The model parameters of the environment types are automatically determined by the system via the model calibration in dynamic environment. Using the model in that way has the following advantages:

- It allows to define environments with non-homogeneous attenuation properties, similar to the real environments.
- The dynamics of the environment can be detected and modeled better. Multiple environment types allow for more fine granular estimation of the real environment.

There are two cases for the calculation of the average radio signal strength at a service location:

- Single environment type: when the path from the the transmitter to the the receiver passes only one environment type we use the original model (equation 4.1).

- Multiple environment types: when the path from the the transmitter to the the receiver passes multiple environment types, we extend the original model equation to the following equation:

$$P(d) = P(d_0) - \sum_{i=1}^{S}[(10n_i \log_{10}(\frac{d_i}{d_{i-1}})] + X_{\sigma_C} \tag{4.2}$$

$P(d)$ is the average radio signal strength at distance d. $P(d_0)$ is the average radio signal strength at a reference distance d_0. S is the number of segments on the direct ray from the transmitter to the receiver. These segments are a result of the intersection of the ray with the borders of the subareas. For instance, ray 1 in figure 4.3 has three segments and ray 2 has four segments. n_i is the path loss exponent of the environment type of the respective segment. d_i is the distance from the transmitter to the end of segment i. X_{σ_C} is a zero-mean normally distributed random variable with standard deviation σ_C, used for modeling the shadowing effect from multiple environment types.

Proof. Derives the model's equation from the original path loss model.

Let a ray have S segments. Each segment has model parameters n_i and σ_i, $i = 1...S$. d_i is the distance from the transmitter to the end of segment i. For the first segment we calculate the signal strength at distance d_1 by applying the original model:

$$P(d_1) = P(d_0) - 10n_1 \log_{10}(\frac{d_1}{d_0}) + X_{\sigma_1} \tag{4.3}$$

$P(d_0)$ is the reference signal strength at some position close to the transmitter (1 meter). Then we calculate the signal strength at the end of the second segment $P(d_2)$ by using the original model. For reference signal strength, we do not use $P(d_0)$ but we use the signal strength at the end of the first segment $P(d_1)$. This is a correct way, since the original model does not specify the distance d_0. It gives this choice to the user. For multiple environment types, we use respectively the beginning of a new environment type.

$$P(d_2) = P(d_1) - 10n_2 \log_{10}(\frac{d_2}{d_1}) + X_{\sigma_2} \tag{4.4}$$

We repeat this calculation for every segment. For the calculation of the signal strength at the end of the i -th segment, we use the original model. For the reference signal strength, we use the calculation for the previous segment:

$$P(d_i) = P(d_{i-1}) - 10n_i \log_{10}(\frac{d_i}{d_{i-1}}) + X_{\sigma_i} \tag{4.5}$$

When we recursively replace the known terms in these equations, we obtain the following equation for $P(d_S)$ which is equivalent to $P(d)$:

$$P(d) = P(d_S) = P(d_0) - \sum_{i=1}^{S}[(10n_i \log_{10}(\frac{d_i}{d_{i-1}})] + \sum_{i=1}^{S} X_{\sigma_i} \quad (4.6)$$

The sum of the random shadowing factors can be expressed as a single random variable. According to the central limit theorem, the sum of S independent and identically distributed random variables is a random variable with normal distribution [137]. In our case, all shadowing factors are independent because they model different environment types. The shadowing factors are identically distributed, as they all are normally distributed. Therefore, we model the shadowing effect as a single normally distributed random variable X_{σ_C}, where σ_C is the combined standard deviation from multiple environment types. We determine σ_C from measurements as described in section 4.3. Finally, the model equation becomes:

$$P(d) = P(d_0) - \sum_{i=1}^{S}[(10n_i \log_{10}(\frac{d_i}{d_{i-1}})] + X_{\sigma_C} \quad (4.7)$$

□

4.2.4. Model-based Error Detection

For error detection, we need a reliable radio coverage assessment. This means an assessment which guarantees that the radio signal strength is above some level. In order to guarantee a reliable assessment, we use the probabilistic model outcome in a way that express the confidence of the assessment. For the assessment, it is important to know whether the average radio signal strength $ARSS$ is greater than the predefined level ($ARSS_{Min}$ for correct service and $ARSS_{RED}$ for redundancy). For this purpose, we use the normal distribution function (Φ-function) [138] which determines the probability of a normally distributed random variable exceeding a particular value. We calculate the probability of an error and the probability of a normal state in the following way:

$$P(Error) = \Phi(\frac{ARSS_{Min} - RSS_{mean}}{\sigma}) \quad (4.8)$$

$$P(Normal) = \Phi(\frac{ARSS_{RED} - RSS_{mean}}{\sigma}) \quad (4.9)$$

where RSS_{mean} is the distance-dependent mean of the signal strength predicted by the model without the shadowing factor (from equations 4.1 and 4.2 for single and multiple environment types respectively). σ is the respective standard deviation. If the calculated probability of an error is higher than a user-defined value, then we have an error.

The Φ-function can be derived from the error function in the following way:

$$\Phi(z)=\frac{1}{2} - \frac{1}{2}erf(\frac{z}{\sqrt{2}}) \quad (4.10)$$

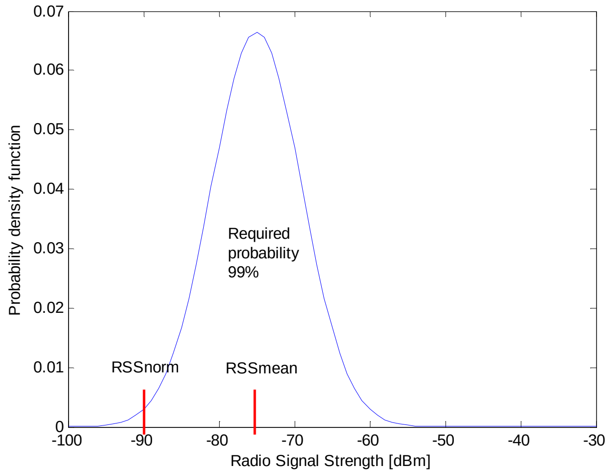


Figure 4.4.: The planned signal strength RSS_{mean}ensures that the actual signal strength RSS_{RED} is above -90dBm with probability of 99%

4.2.5. Model-based System Recovery

Another important model usage is during the base station planning (section 5). In this phase, the requirement is to determine an infrastructure that satisfies the requirement:

$$P(ARSS > RSS_{RED}) > Prob_{req} \tag{4.11}$$

The user specifies $Prob_{req}$ and RSS_{RED}: a required probability $Prob_{req}$ that the signal strength exceeds some specific value RSS_{RED}. But the base station planning algorithm requires some deterministic condition for the signal strength. From the model and the standard deviation we determine a value for RSS_{mean} which can be used for the planning. RSS_{mean} is calculated in such a way that if the base station planning algorithm ensures the requirement $\overline{ARSS} \geq RSS_{mean}$, then $ARSS > ARSS_{RED}$ with probability P_{req}. We calculate RSS_{mean} by using the inverse error function:

$$RSS_{mean} = RSS_{RED} - \sqrt{2}\sigma erfinv(\frac{\frac{1}{2} - Prob_{req}}{\frac{1}{2}}) \tag{4.12}$$

Example 1. If the requirement is $RSS_{RED} > -90dBm$ with probability of $P_{req} = 0.99$ and the standard deviation of the model is $\sigma = 6dB$, then from equation 4.12 we determine $RSS_{mean} = -76dBm$. This means that if the base station planning ensures that the mean signal strength is at least $-76dBm$, then it is with 99% sure that the real signal strength is above $-90dBm$. This aspect is graphically illustrated on figure 4.4.

4.2.6. Extension of the Fault Definition

At this stage, we have to make another justification for the faults. We distinguish between short-term environmental dynamics and long-term environmental dynamics. The short-term environmental dynamics are part of the usual system operation. These are for instance, the every-day movement of trucks and goods within the facility. The short-term environmental dynamics are compensated by the redundancy. It is not desired to initiate a recovery during the usual operations. The long-term environmental dynamics are caused by reconstruction, extension of production lines, etc. We consider only the long-term environmental dynamics as faults. In order to distinguish the short-term faults from the long-term faults we use the user-defined variable T_{perm}. If the environmental dynamics persist for a time interval longer than T_{perm}, then this is a permanent fault.

4.3. Parameter Calculation Method

In this section, we will formally describe the method for radio model parameter calculation from a set of signal strength measurements. We represent the problem as a linear optimization problem and solve it using linear least squares optimization with parameter bounds and inequality constraints. This method is used for both infrastructure-based measurement and localization-based measurements.

The radio propagation model has the following equations for estimating the received signal strength at a receiver:

- Case 1: when the path from the transmitter to the receiver (T-R path) passes only one environment type, we use the original model (equation 4.1).

- Case 2: when the T-R path passes multiple environment types, we use our extended application of the original model (equation 4.2).

In the case of infrastructure-based measurements, the transmitter and the receiver are the base stations. In the case of localization-based measurements, the radio signal strength is measured at the base stations; so the transmitter is a mobile station and the receiver is a base station. The reverse is also possible, if the ARSS is measured at the mobile stations.

The model parameters that have to be determined are:

- The path loss exponents n_j and the standard deviations σ_j for every environment type $j \in [1...|N|]$. N is a vector of environment types, $|N|$ is the number of environments (number of elements in N).

- The standard deviation for the case that the T-R path passes multiple environments σ_C

In order to determine these parameters, our method requires a set of reference signal strength measurements. Every measurement contains the following information:

- the coordinates of the transmitter
- the coordinates of the receiver
- measurement result
  - if the receiver received frames from the transmitter for some time period, then this is the average radio signal strength. These results are stored in a vector V.
  - if the receiver did not receive any frames from the transmitter, the result is "non-covered". These results are stored at the vector Q.

Our approach for model calibration is to first determine the path loss exponents in such a way that the model results and the measurement values in V are as close as possible. For this purpose, we define a system of linear equations from the measurement values in V, the model, and the path loss exponents in N. The variables in this system are the path loss exponents n_j for $n_j \in N$. This system is overdetermined, since the measured values are more than the environment types ($|V| > |N|$). This is because in general, there are multiple measurement values for each environment type. Since this system is overdetermined we solve it by using a least squared method. This means that the solution minimizes the sum of squared differences between the measured values and the model predictions. The residual is the difference between the measured values and the model predictions. We determine the standard deviations of the model from the variation of the residual. In addition, we use the vector Q in order to define constraints to the least squares solution. These constraints allow the model to preserve the measured non-coverage situations from the real system.

We derive the following system of linear equations from all measurements in V:

$$P(d) = V \tag{4.13}$$

When $P(d)$ for every measurement is replaced by the respective model equation, the linear system is transformed to:

$$P(d_0) - CN = V \tag{4.14}$$

which is transformed to:

$$CN = P(d_0) - V \tag{4.15}$$

The linear system 4.15 contains an equation for every measured value in the vector $v_i \in V$. The left-hand side of the equation describes the model-predicted path loss which is the difference between the reference signal strength $P(d_0)$ next to the transmitter and the measured signal strength at the receiver in V. C is a matrix of model-dependent constants. The unknown parameters in N affect only the path loss. The model-predicted path loss (left-hand side) is put equal to the measured path loss (right-hand side). Every equation in 4.15 has the following form:

$$c_{i,1}n_1 + c_{i,2}n_2 + ... + c_{i,|N|}n_{|N|} = P(d_0)_i - v_i \tag{4.16}$$

In this equation the constants $c_{i,j}(i = [1...|V|], j = [1...|N|])$ are the model-dependent constants based on the distance. We determine them from the model, using information about the transmitter and receiver coordinates and the number and type of ray-segments along the path from the transmitter to the receiver. For the calculations of $c_{i,j}$, we have two cases that depend on the used model equation:

- Case 1: for rays passing a single environment type n_j, the constant $c_{i,j}$ is calculated as:

  $$c_{i,j} = 10\log_{10}(\frac{d}{d_0}) \tag{4.17}$$

  which follows from equation 4.1. All other constants are zero, since the other environment types do not influence the considered measurement.

- Case 2: in the general case, the ray passes multiple environment types, $c_{i,j}$ is the sum of model constants over all subareas with environment type n_j (from equation 4.2):

  $$c_{i,j} = \sum 10\log_{10}(\frac{d_l}{d_{l-1}}) \tag{4.18}$$

$P(d_0)$ is a known constant for every T-R combination (see section 4.2).
We apply the following constraints to the solution of this system:

- Parameter bounds for keeping the path loss exponents in a realistic range:

  $$n_{low} \leq n_j \leq n_{up} \tag{4.19}$$

  These constraints ensure that the radio propagation model has realistic parameters. The values of n_{low} and n_{up} have to be determined by an expert during the network deployment. $n_{low} = 2$ is the value for radio propagation in vacuum (no obstacles). Measurements in different environments have resulted in values for $n_{up} = [3.3...5]$[108][10].

- Inequality constraints for preserving the non-coverage situations from reality in the model (inequality 4.22, derived from 4.20 and 4.21). For all measurement results in Q we have:

$$P(d) < P_{min} \tag{4.20}$$

$$P(d_0) - CN < P_{min} \tag{4.21}$$

$$CN < P(d_0) - P_{min} \tag{4.22}$$

P_{min} is the minimum signal strength value that can be measured by the wireless adapter of the receiver. This constraint specifies that the measured non-coverage situations are represented by the model. It results in a system of linear inequalities. The left-hand side is equal to the left-hand side of equation 4.15. The right-hand side expresses the measured maximum path loss.

In this way, we transform the radio model calibration problem into a least squares problem (equation 4.15) with constraints (equations 4.19 and 4.22). We solve this problem by applying an active-set optimization method originally published in [68] and extended within MATLAB [96] for equality and inequality constraints. The method operates in two phases. In the first phase, it finds an initial feasible point (a solution that satisfies all constraints). In the second phase it iteratively generates a sequence of feasible points which converge to the solution of the problem.

The solution of the least squares problem is the set of path loss exponents. The next step is to determine the standard deviations of the propagation model. We determine the standard deviations of the model from the variation of the residual. The residual is the difference between the measured values and the model predictions which results from the fact that the linear system is overdetermined. For a given path loss exponent n_j, the residual is given as:

$$Residual = Cn_j - V_j \tag{4.23}$$

which is over all measured signal strength values V_j within environment type n_j. We estimate the parameters of a normal distribution (mean and standard deviation) which fit these values in $Residual$. For this purpose we use a normal distribution parameter fitting function. The model parameter σ_j is the obtained standard deviation of this distribution, since it describes the variation of the model predictions about the distance dependent mean. We estimate the standard deviation for multiple environment types σ_C from the residual from all measurements, including multiple environment types.

Optimization method discussion In the general case the solver finds a solution of the defined optimization problem. The lower bound constraints and the inequality constraints are feasible, since they regulate the solution in the same direction (see figure 4.5). The only possible case of infeasibility is when some inequality constraint is not

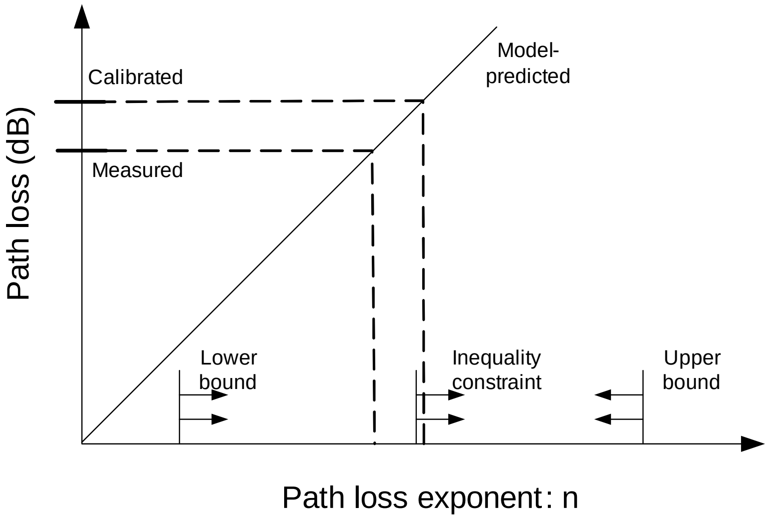


Figure 4.5.: Radio model calibration

consistent with the upper bound. In this case the following solutions are possible from which the user chooses at design time:

1. The upper bound is increased so that it is consistent with the inequality constraint. This is the pessimistic choice and the default choice.
2. The measurement leading to inconsistency is considered an outlier and is not used for the calibration. This is an optimistic choice.
3. Expert mode: the user is asked to decide between 1 and 2 at runtime.

Since the model is linear in terms of the unknowns $n_j \in N$ (see equation 4.16), the minimum found by the linear least squares minimization is always a global minimum.

4.4. Automatic Localization for Model Calibration

This section describes how locations of the mobile stations are determined. In addition, it shows how to derive radio signal strength measurements for model calibration from the localization. This section begins with the requirements for the localization. The disadvantages of the existing approaches in the context of this thesis have been discussed in section 2.3. Section 4.4.2 provides an overview of the developed localization approach; followed by detailed definitions of the localization steps: Initialization, location estimation, location improvement and interpretation of the results (sections 4.4.3 through 4.4.6). Section 4.5 analyzes the developed localization approach and its integration with the model calibration.

4.4.1. Requirements to the Localization

To use the localization for model calibration, the following requirements have to be fulfilled.

1. The localization should be based on the communication technology. Since the model calibration uses measurements from existing data communications in the network, it is required that the localization is based on the used communication technology (e.g. WLAN).

2. The localization should be accurate enough for model calibration. This means that the inherent localization inaccuracies should not have a negative effect on the model calibration.

3. The general requirements for the thesis (section 1.3) put additional requirements for the localization method:

    a) Dynamic environments

    b) Self-maintainability

    c) Personnel and effort constraints

The disadvantages of existing RSS-based methods (for a discussion see section 2.3) in the context of this thesis are:

- They require manual efforts for the collection of training data in the initialization phase.

- They do not automatically react on dynamic environments. When the environment changes, the training data is out of date and the localization accuracy decreases. The existing methods are not self-maintainable because they do not automatically adapt the training data when the environment has changed. In this case, the initialization phase should be repeated.

- The existing RSS-based localization methods do not consider the interpretation of the location information for model calibration. For this purpose, a new method is needed which copes with the inherent localization inaccuracy and determines ARSS by appropriate grouping of single single RSS-measurements.

For these reasons, we have developed a new localization approach which is specifically tailored at the requirements for this thesis and for the purpose of model calibration.

4.4.2. Overview of the Localization Approach

We will give an overview of our approach by defining its main phases according to our definition of a generic localization system (section 2.3). A graphical representation of our approach, compared to the generic localization systems and the standard RSS-based approaches is given on figure 2.2 on page 29.

In the initialization phase, our approach automatically generates the training data. For this purpose it uses the calibrated radio propagation model (sections 4.2 and 4.3). This model is always an actual representation of the real environment, achieved through automatic reference measurements and model calibration. In this way, the training data is also updated. The basic idea of this method is published in [13]; in [11, 8] we have provided a formal definition and an evaluation of the method. See section 4.5 for analysis on this dependence.

For the location estimation, we use an existing method from the literature: k-nearest neighbors search in signal strength space [42]. In the location estimation phase, the method searches the k-nearest training data sets with respect to the similarity of the ARSS of the base stations. The base stations measure signal strength from the mobile stations and send the measurements to the localization server which is part of the management appliance. The localization server collects measurement time sequences for every mobile station. A measurement time sequence is an array containing measured RSS from a mobile station. For every time instant, the sequence contains RSS for messages, sent by the mobile station and measured by the base stations. The localization server periodically analyzes the measurement sequences and performs location estimation, estimation improvement and interpretation of the localization results. Then it sends the results (ARSS measurements) to the model calibration component.

For the estimation improvement, our method is similar to the methods from the literature in a way that we use Kalman filtering. The different is that our method performs filtering in both directions (forward and backward in time) which is called Kalman smoothing [119]. In a typical localization application the location estimate is used for location tracking (monitoring the locations of objects). Therefore, the goal of a typical localization system is improving *the last* location estimate (the most actual moment in time). For this purpose, Kalman filter has been used [53, 116]. However, our localization system is used for providing measurement data for the model calibration. Thus, our goal is to improve *every* location estimate. A simple way would be to memorize the outcomes of the Kalman filter at every location estimate. However, this would mean that the location estimates at the beginning of a measurement sequence would use less historical information and would be less accurate. Also in this way not all available information is used. Our idea is to perform filtering in both directions (forward and backward in time) which is called Kalman smoothing. Doing this, we utilize the fact that the whole measurement sequence is available during the estimation improvement. The location estimates at the beginning of a sequence have few historical information from the forward direction but they have much more information from the backward direction. The estimation improvement is based on more information and we expect it to be more accurate compared to the filtering approach.

The interpretation phase is specific to our localization system, since the location information is used for a specific purpose: radio model calibration. The interpretation extracts ARSS measurements for model calibration from a set of measurement time sequences with location information. According to [108], the ARSS (average radio signal strength) is determined by averaging signal strength measurements within a radius of 5 to 40 times the wavelength from a given center (for 2.4GHz 0.75 to 5 meters). During the interpretation phase our method groups the RSS-measurements into clusters and averages the RSS measurements within a cluster. Doing this, our method *makes use* of the inherent localization inaccuracy. Instead of choosing a cluster with the required measurement radius, it chooses clusters with a smaller cluster radius which has sufficient measurements. Because of the localization inaccuracy, the real measurements are spread in the required measurement radius.

The combination of location estimation, Kalman smoothing, clustering and signal strength measurements emulate a site survey in an automatic way. The next sections formally define the phases of our localization approach.

4.4.3. Initialization

The initialization phase generates the training data for every training location. The training locations are located at equal distance within the service area in the form of a grid. We denote the training locations as L1. . . Ln.

For every training location L_l, the location estimation method requires the received ARSS at the base stations. The training data is generated by using the propagation model (equations 4.1 and 4.2). Assuming that a mobile station is located at the service location L_l, we calculate a ARSS at every base station. For details on the equation, see section 4.2. The training data for every training location L_l has the following form: $BS_1(ARSS_1), BS_2(ARSS_2)...BS_n(ARSS_n)$.

4.4.4. Location Estimation

During the location estimation phase every BS reports the measured ARSS of the mobile stations to the localization server. For every time instant, this leads to the tuple (MS, (AP1, ARSS1m), (AP2, ARSS2m), ...). The algorithm finds the k nearest neighbors in signal strength space. These are the k training locations that have a training pattern with a smallest euclidean distance to the observed one. This is the distance in signal strength space (see section 2.3 for details). The estimated location is a weighted average of the locations of the k nearest neighbors. The weights are proportional to the proximity in signal strength space. This approach is depicted in figure 2.3. The values of the parameter k are in the range $[2...4]$.

4.4.5. Estimation Improvement

In the estimation improvement phase, we use Kalman smoothing for increasing the accuracy of the location estimation. Kalman smoothing is the application of the Kalman filter on a measurement time sequence in the forward and backward direction.

Kalman filter is a widely used filter for improving the estimation of the real system states, given the noisy observations of these states and a noisy control process [119]. The Kalman filter requires a description of the system's behavior in the form of linear equations. This includes the state equation:

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{4.24}$$

and the output equation:

$$y_k = Cx_k + z_k \tag{4.25}$$

x_k is a vector of system state variables, u_k is a vector of system inputs and y_k is a vector of system outputs for a time instant k. A, B, C are transition matrices describing the system's behavior. w is the process noise and z is the observation noise. Given the noisy observations y, the system inputs u, the transition matrices A, B, C and the description of the noise w and z, the Kalman filter estimates the real state of the system x.

In our localization problem, the system state variables are the real coordinates of the mobile station (X, Y). Since the localization system can not control the movement direction, we do not use the input parameter u. We use the following equations to model the system behavior. The state equation is:

$$\begin{bmatrix} X \\ Y \end{bmatrix}_{k+1} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} X \\ Y \end{bmatrix}_k + w_k \tag{4.26}$$

and the output equation is:

$$\begin{bmatrix} \widehat{X} \\ \widehat{Y} \end{bmatrix}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} X \\ Y \end{bmatrix}_k + z_k \tag{4.27}$$

In the state equation 4.26 the coordinates at the time instant $k+1$ are equal to the coordinates at time instant k plus the movement within time interval $T = [k...k+1]$. This movement is equal to the stations speed multiplied by the time T. The speed of the mobile stations is not known, therefore it is considered as a *process noise*:

$$w_k = T.Speed_k \tag{4.28}$$

The noisy observations $\begin{bmatrix} \widehat{X} \\ \widehat{Y} \end{bmatrix}_k$ are the location estimations for the measurement time sequence. These coordinates are obtained by the location estimation (section 4.4.4). The estimated coordinates are equal to the real coordinates plus the localization inaccuracy. The localization inaccuracy at time instant k is not known, therefore it is considered as *observation noise*:

$$z_k = LocalizationInaccuracy_k \tag{4.29}$$

In order to use these Kalman filter equations for localization the following parameters have to be specified: initial values for the system state $\begin{bmatrix} X \\ Y \end{bmatrix}_0$, process noise w, and observation noise z. For the initial values we use the first location estimate from an observation sequence. The process noise w is described by the expected speed of the mobile stations. The observation noise z is described by the expected localization inaccuracy.

The Kalman filter assumes that the noises w and z have average values zero and that there is no correlation between the two noise sources. In the case of localization these assumptions are correct. Firstly the average values of the noises for a sufficiently long observation window tend to zero. The process noise w is described by the speed of the mobile station which can be in any arbitrary direction. Therefore, it is correct to assume that the sum of all speeds over some time interval is zero. Similarly the observation noise, describing the localization inaccuracy can be in any arbitrary direction. This means that the sum of all localization inaccuracies tends to zero. Secondly, there is no correlation between the two noise sources, since they depend on totally different factors. The process noise depends on the movement direction. The observation noise depends on the location estimation inaccuracy which depends on the training data, the number of base stations, antenna profile and the environment.

The process noise and the observation noise have to be provided in a form of a covariance matrix. The derivation of the noise covariance matrices will be discussed in the following.

Process noise (variance of the speed) The covariance matrix for the process noise is the following:

$$W = T. \begin{bmatrix} cov(w_x, w_x) & cov(w_x, w_y) \\ cov(w_y, w_x) & cov(w_y, w_y) \end{bmatrix} \tag{4.30}$$

w_x and w_y are random variables that describe the speed in the X-direction and in the Y-direction. If detailed movement profiles of the mobile stations are available (e.g. historical data or exact definition), the values of this matrix can be calculated by statistics of the movement profiles. If the movement profiles are not available, a simple but yet effective estimation can be done which we use in this thesis. This estimation is based on the maximum possible speed of the mobile stations $Speed_{max}$. If this is the only available information, we assume that the movement in the X-direction is independent from the movement in the Y-direction. Then the non-diagonal elements of the covariance matrices are zero because the covariance of two independent random variables is zero. The diagonal elements of the covariance matrix are defined by the variance of the noise variables. The covariance of the same random variable is equal to its variance $cov(w_x, w_x) = var(w_x)$. With these considerations, the covariance matrix of the process noise has the following form:

$$W = T. \begin{bmatrix} var(w_x) & 0 \\ 0 & var(w_y) \end{bmatrix} \tag{4.31}$$

$var(w_x)$ is the variance of the speed of the mobile stations in the X-direction. $var(w_y)$ is the variance of the speed in the Y-direction:

$$var(w_x) = var(speed_x) \tag{4.32}$$

$$var(w_y) = var(speed_y) \tag{4.33}$$

Since we do not have any additional knowledge about the speed distribution, we assume a uniform distribution between zero and the maximum speed. The variance of a uniformly distributed random variable in the interval $[a...b]$ is $var = \frac{1}{12}(b-a)^2$ [139]. In the particular case of localization, the direction of movement shall be considered as well. This means that the speed can be positive or negative within a given coordinate system, depending on the movement direction. For this reason, the interval $[-Speed_{max}...Speed_{max}]$ has to be considered:

$$var(w_x) = var(w_y) = \frac{1}{12}(Speed_{max} - (-Speed_{max}))^2 = \frac{Speed_{max}^2}{3} \tag{4.34}$$

Observation noise (variance of the location estimation accuracy) The covariance matrix of the observation noise has the following form:

$$Z = \begin{bmatrix} cov(z_x, z_x) & cov(z_x, z_y) \\ cov(z_y, z_x) & cov(z_y, z_y) \end{bmatrix} \tag{4.35}$$

z_x and z_y are the location estimation inaccuracies in the X-direction and in the Y-direction. The location estimation inaccuracy in the X-direction is independent from the location estimation inaccuracy in the Y-direction. This is because of the location estimation algorithm. The localization inaccuracies can occur equally probable in all possible directions. The estimation method is based on training data which is equally distributed in the service area. Therefore the non-diagonal elements of the matrix are zero. The covariance of the same random variable is equal to its variance $cov(z_x, z_x) = var(z_x)$. With these considerations, the covariance matrix of the process noise has the following form:

$$Z = \begin{bmatrix} var(z_x) & 0 \\ 0 & var(z_y) \end{bmatrix} \tag{4.36}$$

The location estimation inaccuracies are determined at different positions in the environment. At every position, we place a mobile station and perform location estimation during a sufficiently large time interval. The location estimation for every position has some inaccuracy. Then we compute the variation of this inaccuracy in the X-direction and in the Y-direction over all positions:

$$var(z_x) = var(LocationInaccuracy_x) \tag{4.37}$$

$$var(z_y) = var(LocationInaccuracy_y) \tag{4.38}$$

In the above calculations the location estimation inaccuracy has to always be computed with respect to the coordinate system in order to represent the positive and negative directions of the inaccuracy: $LocationInaccuracy_x = Real_x - Estimation_x$.

If such evaluation for determining the location estimation inaccuracy is not feasible (e.g. due to time an effort constraints), an alternative approach is to *estimate* it from existing location estimation experiences in other buildings and environments. If we know that the absolute (directionless) standard deviation of the location estimation inaccuracy in other environments is $LocationInnaccuracy_{std}$, then

$$var(z_x) = var(z_y) = (2\frac{LocationInaccuracy_{std}}{\sqrt{2}})^2 = \frac{LocationInaccuracy_{std}^2}{2} \tag{4.39}$$

The standard deviation is first divided by $\sqrt{2}$ in order to estimate the deviation in the X and Y direction. Then we multiply it by two to account for the positive and negative directions of the inaccuracy. Finally the result is raised to the second power in order to compute the variance. We use the approach in equation 4.39.

4.4.6. Interpretation of Location Information

The interpretation phase is the interface between localization and model calibration. From a given set of measurement time sequences (radio signal strength and location), the interpretation has to extract ARSS measurements for model calibration. According to [108], the ARSS is determined by averaging signal strength measurements within a

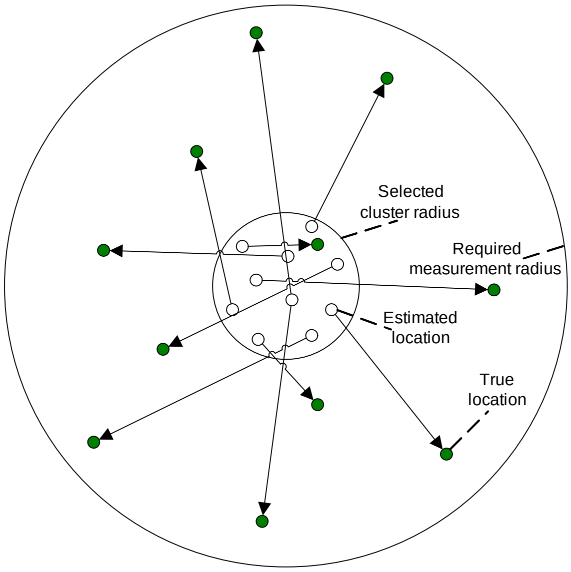


Figure 4.6.: Interpretation of location information: the inherent localization inaccuracy is used to group the RSS measurements in an appropriate way for calculation of ARSS.

measurement radius of 5 to 40 times the wavelength from a given center (for 2.4GHz 0.75 to 5 meters). In addition the interpretation has to cope with the inherent inaccuracy of the localization.

Our approach is to apply clustering for grouping individual RSS-measurements into clusters and then determining the ARSS within a cluster. In order to cope with the localization inaccuracy, we use a smaller measurement radius when selecting the individual RSS-measurements within a cluster. This has two positive effects. Firstly, the localization inaccuracy increases the measurement radius to the required radius. Secondly, the localization inaccuracies occur in different directions. In this way, the RSS measurements within a cluster tend to be equally distributed within the required measurement radius. Figure 4.6 illustrates this concept.

There are different approaches for clustering. Basically the clustering approaches are divided into hierarchical and partitional [123]. Partitional clustering is a division of the objects into non-overlapping groups (clusters) such that each object is part of only one cluster. Hierarchical clustering, on the other hand, creates a hierarchical tree of clusters where each cluster contains sub-clusters which again contain sub-clusters, and so on. We choose hierarchical clustering because it has two important advantages in our particular application. Firstly, it does not require information about the number of the required clusters (as many other approaches do). This fits well in our application. We are not interested in finding some pre-defined number of ARSS measurements. We would rather find clusters of individual RSS-measurements which have a cluster radius smaller than the selected one (see figure 4.6). The second advantage is that the hierarchical methods allow for specifying the clusters according to some property. By cutting the hierarchical tree at some level, it is possible to select clusters with a desired property. Our approach is to cut the hierarchical cluster tree based on the cluster radius. The cluster radius is the distance from the geometrical cluster center to the far most object. The cutoff value for the selected cluster radius is:

$$Cuttoff = 40\lambda - LocalizationInaccuracy_{mean} \tag{4.40}$$

where λ is the wavelength of the operating frequency. $LocalizationInaccuracy_{mean}$ is the expected inaccuracy of the localization which is set by the user based on experience. If, for some values of λ and $LocalizationInaccuracy_{mean}$, the cutoff value is negative, then we propose to use a minimum value of 1m.

All clusters containing more than N_{RSS} measurements are used for model calibration. The interpretation method calculates the ARSS per base station as a mean from all measurements within a cluster. The ARRS value is sent to the model calibration component as a reference measurement for model calibration. The value N_{RSS} is determined by the deployment staff; and it is recommended to select a value of at least 10. When N_{RSS} increases, this leads to better estimate of the ARSS within a single cluster, but this also leads to a decreased overall number of reference measurements. The value of this parameter also depends on the speed of the mobile stations.

4.5. Analysis of the Approach

When the localization is used for the purpose of radio model calibration, the following information flow among the components appears (figure 4.7). Firstly, the radio propagation model is used to generate training data for the localization. Based on the training data and the RSS measurements from the wireless network, the localization component determines respective positions of the mobile stations. The RSS and location information is used by the calibration component to determine the actual model parameters and update the radio propagation model. There is a cyclic dependency between the radio propagation model, localization, and calibration. In this context, it is important to consider what effect the localization inaccuracies have on the radio model calibration.

It should be noted that if the infrastructure-based measurements can detect the environmental dynamics, this cyclic dependency does not occur. Then in the first phase the radio model is calibrated only from the infrastructure-based measurements. In the second calibration phase, the localization-based measurements are used as an additional information. We have shown that when the base stations are located in such a way that

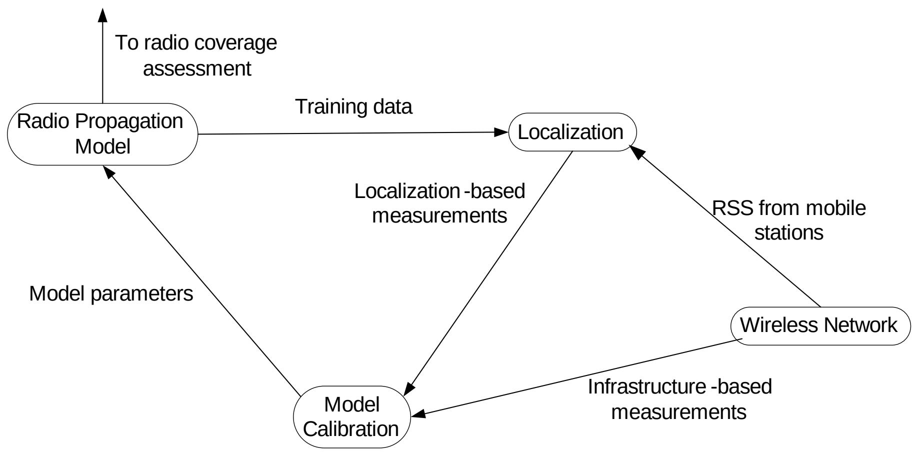


Figure 4.7.: Information flow among the components for radio coverage assessment

the infrastructure-based measurements assess the attenuation of the environment, then the error detection is successful [9] (and section 6.3).

For the case that the infrastructure-based measurements can not be used, we have foreseen the following measures to cope with the localization inaccuracies. Firstly, we apply estimation improvement (Kalman smoothing) to reduce the localization inaccuracies (section 4.4.5). Secondly, we apply an inaccuracy-aware interpretation of the localization results. In the context of this interpretation, localization inaccuracies up to some extent ($LocalizationInaccuracy_{mean}$) can even have a positive effect (section 4.4.6).

In spite of these measures, some localization inaccuracies (above the value $LocalizationInaccuracy_{mean}$) can occur. Our statement is that in spite of these localization inaccuracies, our method for model calibration can calculate the correct model parameters. The following paragraphs propose the reasons for this statement.

The distance inaccuracy is relatively smaller, compared to the localization inaccuracy. In the proposed radio calibration method, the transmitter-receiver (T-R) distance is the main factor in calculating the model parameters (section 4.3, equations 4.15 through 4.18). A given localization inaccuracy leads to some distance inaccuracy. However, in most cases the distance inaccuracy is much smaller than the localization inaccuracy. Figure 4.8 shows an example of this notion. It shows a transmitter, a receiver with its real position and an example of the estimated position. The isolines in the figure show the distance inaccuracy which is possible with a localization inaccuracy within 5 meters. Although the localization inaccuracy is up to 5 meters, a large amount of the distance inaccuracies is within 1 meter (the area around the received in white). This is because the localization inaccuracy can be in different directions. Some directions

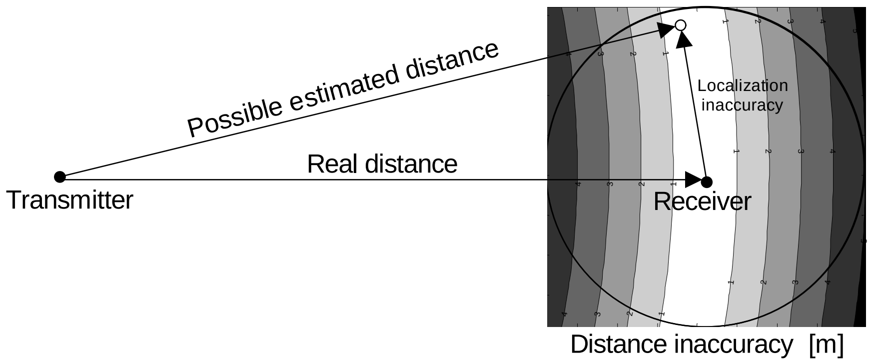


Figure 4.8.: The distance inaccuracy is relatively smaller, compared to the localization inaccuracy

are more beneficial for the distance inaccuracy than others. We have observed that the estimated distance is normally distributed about the real distance with a standard deviation depending on the localization inaccuracy. For instance, if the localization inaccuracy is normally distributed with a mean of $8.3m$ and a standard deviation $2.7m$, then the estimated distance is normally distributed about the real distance with a standard deviation of $6.2m$.

The distance inaccuracy is treated as shadowing. The remaining distance inaccuracy increase the shadowing of the model but lead to nearly the same path loss exponent. This is because the propagation model foresees that the ARSS is normally distributed about a distance-dependent mean. This distribution is modeled by the shadowing deviation factor. This means that, for two close distances, the model predicts two overlapping ranges of ARSS. The distance inaccuracies are in different directions and the parameter calculation method minimizes the differences between the model and the measurements in a least squared sense. Therefore the calculated path loss exponent is nearly the same. The shadowing deviation is increased.

Lets consider an example with one localization-based measurement. The ARSS from one mobile station has been measured at two base stations (see figure 4.9). Firstly we consider the model calibration based on the real location (real T-R distances). The figure shows the linear function of the path loss on the T-R distance. The slope of this line is the value of the path loss exponent. This value minimizes the difference between the model predictions and the measurements. The dark dots lie apart from the straight line because of the shadowing.

We now consider the localization inaccuracy leading to distance inaccuracy. The distance inaccuracy is shown in the figure as white circles moved to the left or to the right from the dark circles. For measurement 1 the localization inaccuracy has increased

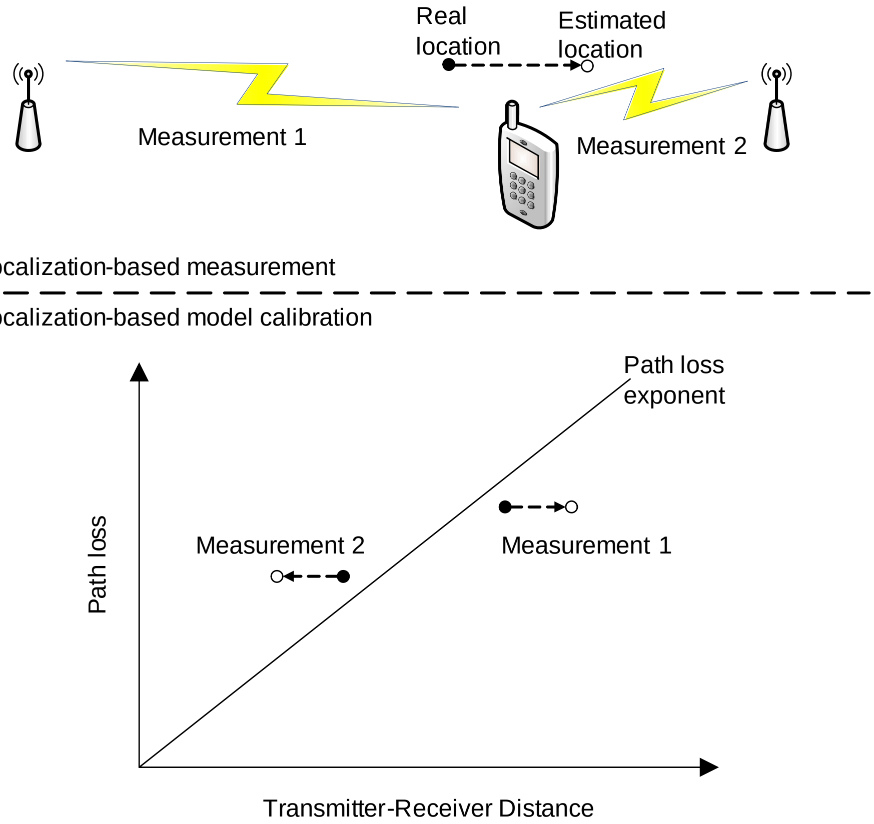


Figure 4.9.: The distance inaccuracy is treated as shadowing. It increases the shadowing deviation but leads to the same path loss exponent.

the T-R distance. For the calibration this means a movement to the right from the linear model. For measurement 2 the localization inaccuracy has decreased the T-R distance. For the calibration this means a movement to the left from the linear model. This has the nice effect that the parameter calculation from the estimated location leads to the same value for the path loss exponent. The distance inaccuracy in this example will increase the shadowing deviation, since the estimated distances have a higher scatter around the linear model than the real distances.

For these reasons we conclude that the localization-based measurements can be used for model calibration.

5. Automatic Base Station Planning

This section describes our algorithm for automatic base station planning. It starts with a problem definition for the base station planning, followed by an overview of our approach in section 5.2. The following sections define the details of the algorithm, namely the used link state model, the optimization approach and the graph consolidation approach. This algorithm is published in [12].

5.1. Problem Definition

The problem of the base station planning algorithm is to find a minimum number of base stations to be installed which transform a wireless mesh network with radio coverage errors and/or connectivity errors to a system without errors. The existing algorithms for this type of problem in wireless mesh networks are computationally intractable, or do not provide the required fault-tolerance (see section 2.4 for a discussion). The following input information is given to the base station planning algorithm:

- Service location information. This is information about the service locations which have to be covered.
- Candidate sites information. This is information about possible locations of the base stations. The candidate sites and the service locations are specified by the deployment staff.
- Radio coverage information. This information is obtained from the radio propagation model (section 4). This is for every service location, the candidate sites which cover this service location, if base stations were installed at all candidate sites.
- Connectivity information: for every candidate site, the candidate sites which have a link in the backbone network, if base stations were installed at all candidate sites. For this purpose, we use our calibrated radio propagation model (section 4) and a link state model (section 5.3).
- The currently installed base stations and their positions

The base station planning algorithm has to determine the number and positions of base stations to be installed such that:

- The radio coverage and the connectivity enter the normal state. The normal state includes redundancy in the services which has been defined in section 3.
- The algorithm should provide an acceptable relation between base stations minimality and running time. The running time of the algorithm should be appropriate for error detection and system recovery in a dynamic propagation environment.

The challenge of the defined problem is the connectivity requirement. The coverage requirement can be formally defined as a local property which depends only on the considered entities (e.g. a base station covers a service location). For the connectivity, the requirement is global. It includes all network paths among all pair of base stations. The existence of a path between two base stations depends not only on the considered base stations, but on the number and positions of all other base stations in the network. The fault-tolerance (biconnectivity) requirement increases the complexity of the problem. It has been shown that finding a minimum number of base stations for this type of problematic is an NP-complete problem. For this reason, we are looking for an approach, having a good balance between minimality and running time.

5.2. Overview of the Algorithm

Our idea is to perform an optimization, satisfying a simple local network property which significantly affects the fulfillment of the global property (biconnectivity). This local property is the *minimum degree.* For the backbone (multi-hop) network, the *degree* of a base station is the number of links to other base stations. The minimum degree of the network is the least degree among all base stations. In graph theory, the minimum degree is a *necessary but not sufficient condition* for k-connectivity [58]. This means that a k-connected graph has a minimum degree of k, but a graph with minimum degree of k is not necessary k-connected. Formally, this rule applies to the backbone of wireless mesh networks. We consider both radio coverage and connectivity. The service locations are spread in some area (e.g. production hall). Hence, the probability that the necessary condition is also sufficient in mesh networks is significantly higher than the probability in graph theory. Therefore, our algorithm fulfills the local necessary condition and checks whether the global sufficient condition is also fulfilled. If not, the algorithm performs an incremental correction. The advantage of this approach is that it fulfills the connectivity requirement without increasing the complexity of the underlying optimization problem.

The algorithm operates in three steps: optimization, connectivity testing, and graph consolidation (figure 5.1). The optimization step finds an optimal solution for the optimization criteria. The optimization criteria are the radio coverage requirement and the *necessary condition for the connectivity* (the local property min. degree). The optimization uses the radio propagation model and the link state model. The connectivity

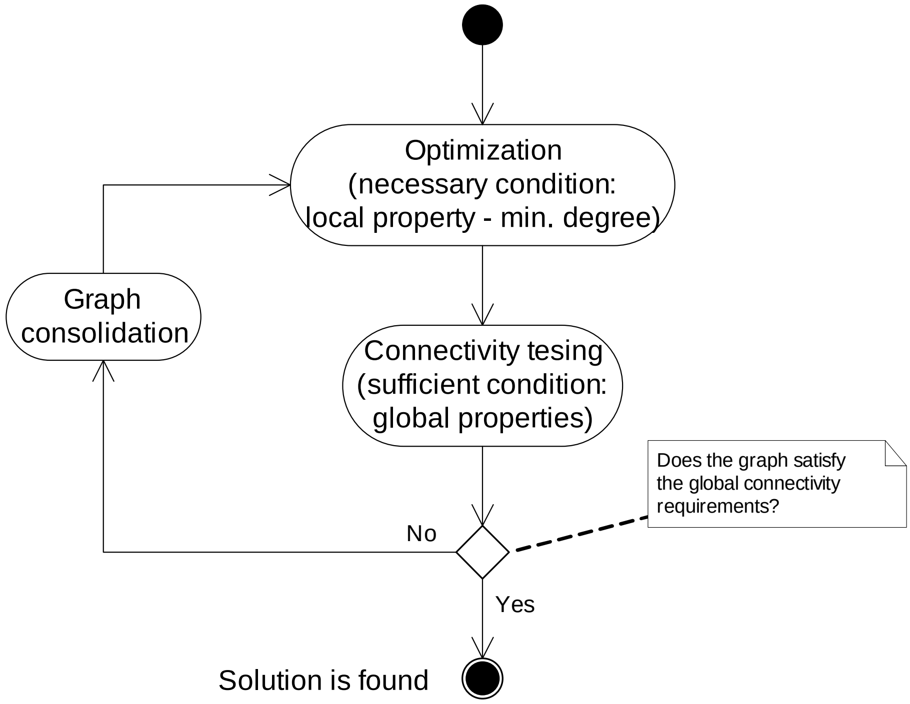


Figure 5.1.: Base station planning algorithm

testing step tests the resulted graph for biconnectivity (the sufficient condition). If the sufficient condition is true, the algorithm finishes. Otherwise the algorithm performs a graph consolidation step. The consolidation step maps biconnected parts of the to a single vertex. After the consolidation, the algorithm continues with the optimization step which is done based on the consolidated graph. After a few (expected 1-3) iterations, the algorithm produces a solution that satisfies the coverage requirements.

Example The optimization step has produced a graph with minimum degree 2 (figure 5.2A) according to the necessary condition. This graph does not satisfy the biconnectivity requirements (one edge and two vertices exist whose removal disconnect the graph). The consolidation step identifies two sub-graphs which are biconnected, and maps them to vertices (figure 5.2B). Note that after the consolidation, the minimum degree of the graph is 1. Then the optimization step places a new base station, such that the consolidated graph plus the new vertex result in a graph with minimum degree of 2 (figure 5.2C). Finally, the deconsolidated graph satisfies the biconnectivity requirements.

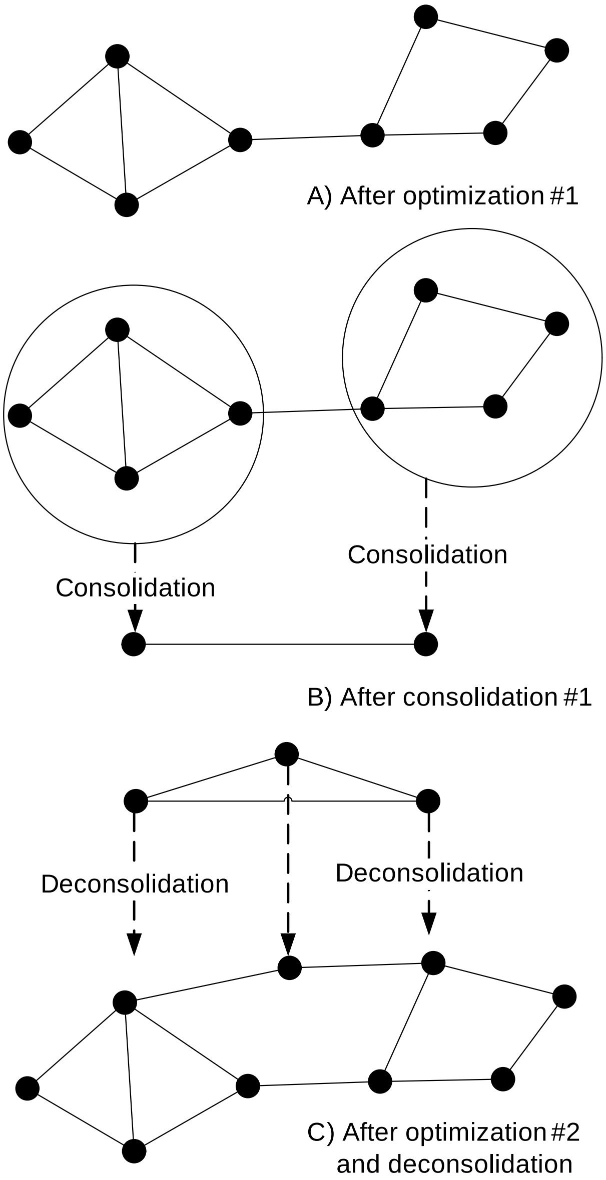


Figure 5.2.: Example operation of the base station planning algorithm

5.3. Link State Model

This section defines the used link model which models the link state based on the radio signal strength. The used link model in this thesis considers the operation of an ad-hoc routing protocol. We have shown in [2] that the communication in a mesh network is possible only if the links have some quality level.

The routing protocols determine the state of a link by analyzing the periodically received Hello packets from the neighbors. Depending on the mobility and the required stability of a link, different approaches for determining the link state at the routing layer exist [86, 147, 37]. What is common for all of them is the analysis of received Hello packets at the routing layer. The AWDS (Ad-hoc Wireless Distribution System) [25][2] routing software, for instance, identifies a link as existing if 10 consequent Hello packets in both directions are received correctly. A link is identified as non existing if 3 consequent Hello packets in either direction are not received.

The radio signal strength is one of the main factors which determine the reception of the packets at the receiver [149]. This means that if the RSS is too low, then the wireless adapter can not decode the frame correctly. Therefore, to model the existence of a link, we use a threshold model based on *ARSS*. If the average radio signal strength exceeds the threshold ($ARSS \geq ARSS_{Min}$), then a link exists, otherwise a link does not exist. Remember that our fault-tolerance approach ensures that $ARSS \geq ARSS_{Min} + \Delta ARSS$.

There are other factors, influencing the packet loss and the link state (e.g. collision, radio interference). But the factor RSS is a *necessary condition* for successful frame decoding. In wireless mesh networks, it is one of the most influencing factors for the link state. This has been shown in our research in wireless mesh network routing [1, 3, 2], wireless network simulation and emulation [7, 20, 21]. Other researchers in our group are working on improving the link state model. They apply a data mining based approach for predicting the link state from various network monitoring information [86].

5.4. Optimization

Minimization approach Our algorithm uses a minimization approach based on binary search for finding the minimum number of base stations (BS_{min}) which satisfies the optimization criteria. It searches iteratively the interval between a lower bound BS_{low} and an upper bound BS_{up}. At each iteration, the algorithm chooses the middle of the interval as a current value for BS and determines whether a solution is possible by solving an optimization problem. If the solution satisfies the optimization criteria, then the algorithm decreases BS by searching the lower half of the interval, otherwise it increases BS by searching the upper half of the interval. Finally, the algorithm finds a minimum value for BS which satisfies the optimization criteria.

Optimization problem formulation The optimization performed at each iteration can be defined by the following:

- Variables

  The optimization variables are the positions of the base stations $(X, Y, Z)_{BS}$. We consider a typical multi-hop network, operating in a single frequency. Therefore, the frequency assignment is a constant for all base stations.

- Bounds

  The variables have lower and upper bounds according to the candidate sites information, provided by the user. For instance, if the base stations are to be installed on the ceiling of a production hall with dimensions 200x300x6m, then the bounds are: $0 \leq X \leq 200$, $0 \leq Y \leq 300$,$Z = 6$. For the currently installed base stations, the lower and upper bounds are equal to the base stations coordinates. In this way, they are considered in the solution, but are not relocated by the algorithm.

- Service locations

  The service locations, defined by their coordinates, are stored in the set SL.

- Radio coverage model

  From the values of the variables $(X, Y, Z)_{BS}$ the radio coverage model provides the radio coverage by the function $Model.RadioCoverage((X, Y, Z)_{BS})$. The result is a vector. For every service location in the set SL, it contains the number of base stations that cover this service location. The calculation is based on the calibrated radio propagation model.

- Connectivity model: $Model.BSDegree((X, Y, Z)_{BS})$. The result is a vector. For every base station, it contains the number of links to other base stations. The calculation is based on the calibrated radio propagation model and the link state model.

- Objective function

  The objective function (Matlab pseudo code in algorithm 5.1) influences the solution in a direction which satisfies the optimization criteria (the coverage requirements and the necessary condition for connectivity). In addition, the objective function maximizes the mean radio coverage degree and the mean backbone degree. The radio coverage degree is the number of base stations covering a service location. From the input coordinates, the radio coverage model and the link state model, the function calculates the radio coverage degree and the backbone degree. For base stations which have less than $N_{bb} = 2$ links to other base stations, the function calculates the backbone shortfall. This is the sum of the differences

Algorithm 5.1 Objective function of the optimization step

```
function Objective (X, Y, Z)
{
PenaltyCoverage = 50;
PenaltyConnectivity = 100;
Coverage = Model.RadioCoverage(X, Y, Z);
Connectivity = Model.BSDegree(X, Y, Z);
ShortfallCoverage = sum(Nlm -
      Coverage(find(Coverage < Nlm)));
ShortfallConnectivity = sum(Nbb -
      Connectivity(find(Connectivity < Nbb)));
Objective = mean(Coverage)
            + mean(Connectivity)
            - PenaltyCoverage*ShortfallCoverage
            - PenaltyConnectivity*ShortfallConnectivity;
}
```

between the required and the current degree over all base stations. The shortfall is weighted by a backbone penalty factor and subtracted by the objective function. The penalty factor is a relatively large number, compared to the mean values which influences the solution to a direction of a zero shortfall. The processing for the radio coverage links is similar. The objective function should be maximized.

Optimization problem solving In order to solve this optimization problem, we apply an optimization method. Specially for this problem is that the objective function can not be differentiated. This is because the objective function, can not be represented as an algebraic function of only the optimization parameters $(X, Y, Z)_{BS}$. This is because the objective function contains the radio coverage model which includes the geometry of the model. Several algorithms exist for solving this type of problem (pattern search, genetic algorithm, simulated annealing). We have selected pattern search, because it has a proven convergence and supports any type of constraints [97].

5.5. Connectivity Testing

For k-connectivity testing in a graph with n vertices, we use existing algorithms from the graph theory [61]. The complexity of this algorithm is $O(k * n^3)$, under the condition that $k < \sqrt{n}$ which is true in our case.

5.6. Graph Consolidation

In this step, the algorithm finds sub-graphs satisfying the connectivity requirements and transforms each subgraph into a single vertex. The formal specification of the graph consolidation step is described by pseudo code in algorithm 5.2 which is explained in the following list. Figure 5.3 shows an example of the operation of the graph consolidation step.

1. Given a graph G, identify all biconnected components G_c containing at least 3 vertices and store them in a set BC. For finding biconnected components, existing graph theory algorithms are used.

2. Identify the *special articulation points* which are articulation points shared between the biconnected components in the set BC. An articulation point is a vertex whose removal disconnects a graph. On figure 5.3B) vertices 1, 2 and 3 are articulation points. Vertex 1 is a special articulation point, since it is shared between two biconnected components of size of at least 3. For identifying biconnected components and articulation points existing graph algorithms are used [125].

3. Every vertex which is either a special articulation point or other vertex, not belonging to a biconnected component in BC, is directly transformed into a vertex in the consolidated graph. The consolidated vertex inherits all edges of the original vertex.

4. For every biconnected component in the set BC:

   a) If it contains special articulation points, then they are removed from the component.

   b) All vertices from the component are transformed into a single vertex in the consolidated graph.

   c) The consolidated vertex inherits all edges of the original vertices to other vertices in the graph. Other vertices are vertices not belonging to the same biconnected component.

   d) Duplicated edges in the consolidated graph are removed.

Algorithm 5.2 Pseudo code of the graph consolidation step

1. $BC = find.biconnected.components(G, |G_c| \geq 3)$
2. $V_{sap} = find.articulation.points(G, shared.among(G_c \in BC))$
3. $foreach\ \ v \in V_{sap} \cup (V(G) - V(BC))$:
   a) $v \rightarrow v^{'}$
   b) $E(v^{'}) = E(v)$
4. $foreach\ \ G_c \in BC$:
   a) $G_c = G_c - V_{sap}$
   b) $G_c \rightarrow v^{'}$
   c) $E(v^{'}) = ExternalEdges(G_c)$
   d) $remove.duplicate.edges(v^{'})$

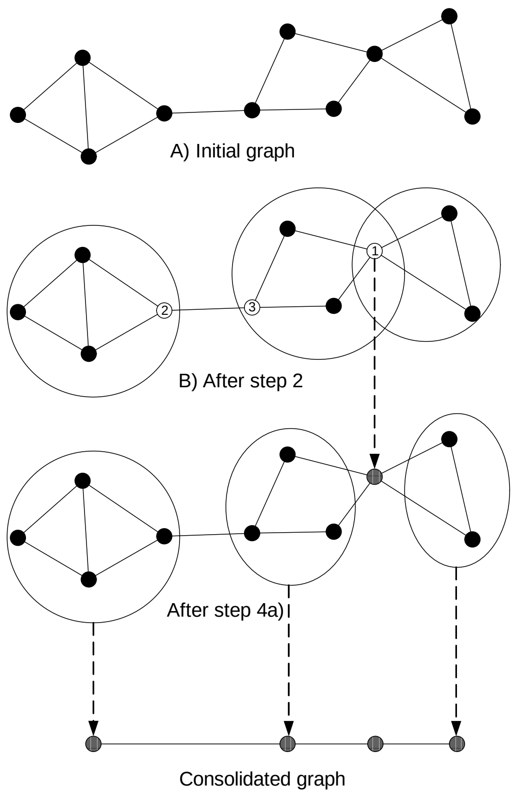


Figure 5.3.: Example of the graph consolidation step

6. Experimental Evaluation

In this section, we will evaluate the key components of our fault-tolerance approach in order to prove its validity. Firstly, we will describe our implementation prototype and explain the structure used for presenting the experiments. In the following three sections, we will evaluate the key components of our fault-tolerance approach. In section 6.3, we will evaluate our infrastructure-based error detection approach. In section 6.4.4, we will evaluate the location-based error detection. In section 6.5, we will evaluate our base station planning algorithm, used for system recovery.

6.1. Implementation Prototype

For the purpose of evaluation, the proposed concepts have been prototypically implemented. Figure 6.1 shows an overview of our implementation: the components and the interactions among them. The following components can be identified.

The *extended Wireless Simulation Tool (eWST)* is a central component running at the management appliance. It is a tool with a GUI performing basic and advanced functions. The basic functions are infrastructure editing (Base stations, antennas), environment editing (building-plan, scale, different environment types and walls), radio propagation calculation and visualization in different views. For these basic functions we have used the Wireless Simulation Tool (WST). WST is a professional software for radio coverage planning of industrial wireless networks developed by rt-solutions.de and used by Phoenix Contact (a leading manufacturer of industrial wireless components). The University of Magdeburg participated in the development of WST as a subcontractor for the radio propagation modeling. This project gave us lots of insights on the requirements for radio coverage deployment and radio coverage maintenance in industrial automation scenarios [24]. We have extended this tool for the advanced features required for radio coverage modeling in this thesis. The functions are: automatic import of infrastructure-based measurements and localization-based measurements; generation of training data for the localization and exporting it to the computing library. WST is implemented in C# and uses the Windows operating system. The interface to the computing library has been implemented by using Windows inter-process communication (COM Automation). The interface to the measurement components has been implemented by using network sockets and import of measurement data in text file format.

The *computing library* is a central component that performs various computing tasks for error detection and system recovery. This library has been implemented in Matlab. Its functions include: linear least squares optimization for the purpose of model calibration; location estimation, Kalman filtering, Kalman smoothing and hierarchical clustering for the purpose of localization. The automatic base station planning algorithm is also implemented in this library. It uses pattern search optimization from Matlab and the MatlabBGL graph library for biconnectivity testing.

The *infrastructure measurement* component is a distributed application running at the base stations. It performs radio signal strength measurements and sends the results to the eWST. The application measures the radio signal strength of the packets, received from other stations. These are the infrastructure-based measurements and localization-based measurements. The packets, used for RSS-measurements, are part of the network traffic. We use the beacons, sent periodically by each BS. We use data packets, sent periodically by the mobile stations. We used a WLAN interface in monitoring mode and read the radio signal strength value from the monitoring (Prism) header. This value is provided by the WLAN card driver for every packet. The wireless interfaces of the BS were simultaneously used in ad-hoc and in monitoring mode (due to the employed madwifi.org driver). For processing the packets and extracting the RSS value from the monitoring header, we used the scapy library of python. All the base stations were timely synchronized via NTP (Network Time Protocol). The purpose of this synchronization is that the management appliance has a synchronized global view on the measured signal strength of all base stations. The update period of the signal strength information is one minute. For this reason, the synchronization precision of NTP was sufficient.

The *mobile measurement tool* has been developed for the purpose of manual radio signal strength measurements which are required for the evaluation. It is a tool with a GUI which enables the user to perform radio signal strength measurements in the service area. It uses a building plan with a scale to represent the coordinate system. The user can perform two measurement profiles: static and mobile. The static profile has been developed for measuring the ARSS at fixed positions. The user selects the location on the map and the tool measures RSS of all base stations for a specified time (default is 60 seconds) using the same measurement method from the monitoring component (WLAN card in monitoring mode, RSS from prism header). The mobile measurement profile has been developed to measure RSS time sequences of mobile stations. The user starts the measurement by clicking on the map and starts moving in the

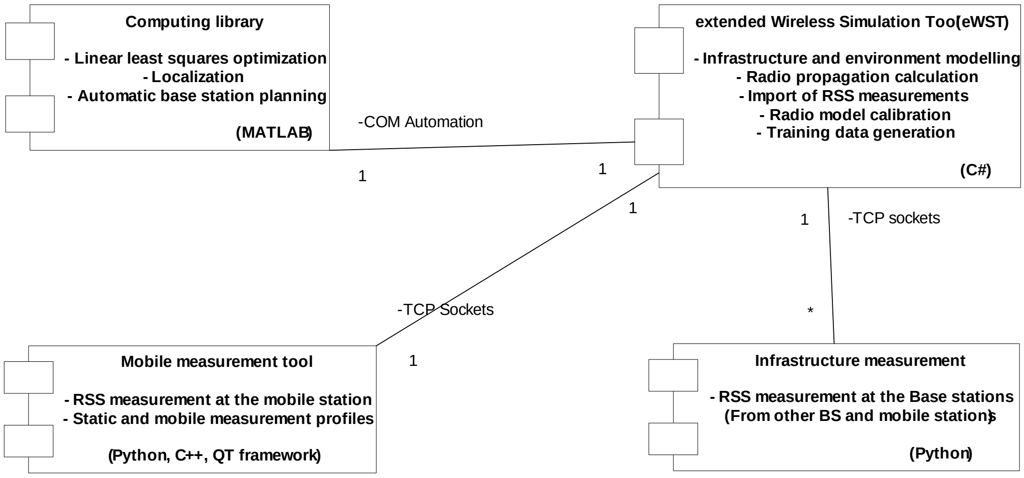


Figure 6.1.: Overview of the implementation prototype

environment. During the movement, the user periodically provides its current location by clicking on the map. During the movement, the tool continuously measures RSS and associates the measurements to the last location information, provided by the user. The mobile measurement profile has been developed for evaluating our localization-based error detection approach. This component has been implemented on Linux using C++ and the QT library for the graphical user interface. This component is a part of a tool-set for evaluation of location estimation algorithms. It has been developed within the diploma thesis [121].

The wireless mesh network has been implemented by using the AWDS (Ad-Hoc Wireless Distribution System) multi-hop routing software which has been developed in our research group [25].

6.2. Structure of the Experiments

The description of the following experiments is structured in the this way.

Purpose of the experiment This section describes the goal of the experiment. This shows which concept will be evaluated and why it is important.

Evaluation approach This section describes our approach for achieving the goal of the experiment. It describes the invented evaluation scenario. It discusses why it is appropriate for achieving the goal of the experiment. It explains what result from this scenario would mean that the concept is successful.

Implementation of the evaluation scenario This section gives details on how we have implemented the evaluation approach

Evaluation results This section presents the results from the evaluation.

Conclusions from the evaluation This section makes a conclusion of the experiment regarding the evaluated concept.

6.3. Infrastructure-based Error Detection

6.3.1. Purpose of the Experiment

The goal of this experiment is to evaluate the infrastructure-based error detection for radio coverage errors. This is an essential part of the fault-tolerant approach described in section 3.

6.3.2. Evaluation Approach

The error detection uses a model-based assessment, based on the calibrated radio propagation model (section 4). Our evaluation approach is to compare the assessed service state (based on the model) to the real service state (from the manual measurement). We make this comparison for different service locations. The possible outcomes from this comparison are shown in table 6.1.

The assessment is correct, if the assessed state is equal to the real state (the main diagonal in table 6.1). If the assessment is not correct, then two cases are possible which are both undesired, but in a different way. The first case is false positive (or underestimation). In this case the real radio coverage is *better* than the assessment. This case includes the positions *above* the main diagonal in table 6.1 (for instance the real state is *normal* but the assessment is *error*). The false positives would initiate unnecessary recoveries and would cause increased maintenance overhead, but they are not critical for the service, since the radio coverage is better than assessed. The second case is false negative (or overestimation). In this case the real radio coverage is *worse* than the assessment. This case includes the positions *below* the main diagonal in table 6.1 (for instance the real state is *error* but the assessment is *normal*). The false negatives are critical, because the errors are not detected. The criteria for successful radio coverage assessment are that the majority of the assessments are correct and the false negatives are a very small portion (up to 5%). The criteria for a successful error detection is that all errors are detected.

Real state: Assessed state:	Failure	Error	Normal
Failure	Correct	False positive (underestimation)	False positive (underestimation)
Error	False negative (overestimation)	Correct	False positive (underestimation)
Normal	False negative (overestimation)	False negative (overestimation)	Correct

Table 6.1.: Possible outcome from the assessment verification

We have compared our approach with the state of the art approach for radio coverage assessment. The state of the art approach is to use the default value for the path loss exponent (PLE=2) and an assessment without confidence level.

We expect that our approach will be successful. Firstly because the radio model has been calibrated to the real measurements (section 4.3). This minimizes the difference between model prediction and reality and we expect that most assessments will be correct. And secondly, our assessment approach provides a confidence parameter (section 4.2) which reduces the false negatives.

6.3.3. Implementation of the Evaluation Approach

We have implemented the evaluation approach in several scenarios (1 office and 2 industrial environments). Table 6.2 shows the parameters of the different scenarios.

In every scenario we have installed a wireless mesh network in the respective environment. The evaluation included two steps. Firstly we performed a radio coverage assessment in the WMN at a given time instant. Secondly, we manually measured the ARSS at some measurement locations (which are selected service locations) and verified the correctness of the assessment. Because of the spacial aspect of the radio coverage, the measurement locations are spread through the entire service area. Therefore the manual measurement process takes some time. For a correct verification it is required that the environment remains unchanged from the time of the assessment until the time when all ARSS measurements are done. For this reason we performed the evaluation in a static environment. Note that for evaluation of the error detection, a dynamic environment is not needed, because the purpose is to evaluate the assessment function at a given time instant. For every measurement location we determined the state of the radio coverage. The service state has been determined, as it has been defined in section 3.1.1 with a minor change. We have added the requirement, that in the normal state two base stations should

Parameter	Scenario 1	Scenario 2
Building and location	University of Magdeburg, Computer science faculty, Magdeburg, Germany	Galileo-Testfeld Sachsen-Anhalt, logistics lab [33], Magdeburg, Germany
Environment type	Office	Industrial
Dimensions of the building	82x33m	40x25m
Size of the service area	$\sim 1600m^2$	$\sim 1000m^2$
Number of base stations	7	4
Operating frequency [GHz]	2.4	5
$ARSS_{RED}$ [dBm]	-63dBm	-63dBm
$ARSS_{Min}$ [dBm]	-78dBm	-78dBm
Number of measurement locations for evaluation	63	34
Environment types	1 Brick walls, 1 Concrete walls, 1 Corridors	1 Logistics hall
Reference radio signal strength at the base stations $P(d_0)$ [dBm]	-38.4 dBm	-38.4 dBm
Reference radio signal strength at the mobile station $P(d_0)$ [dBm]	-42.5dBm	-42.5 dBm

Table 6.2.: Parameters of the evaluation scenarios for radio coverage assessment

be reachable. This is important from the practical point of view for tolerating crashes of the equipment.

For every scenario we have defined the coordinates of the different environment types based on our knowledge and observations about the building material and obstacles. Note that we did not define the model parameters - this is done automatically by the model calibration. For instance in the building on figure 6.2,B two environment types have been defined: offices with brick walls (old part of the building) and offices with concrete walls (new part of the building).

Then the base stations have made automatic infrastructure-based measurements and have sent the results to the eWST tool. This software has automatically calibrated the radio propagation model (using the method described in section 4.3).

Determining the evaluation parameters We have measured the reference radio signal strength $P(d_0)$ at a reference distance $d_0 = 1m$. The constants $P(d_0)$ and $ARSS_{Min}$ have been determined per scenario, since different hardware was used.

We have determined a value for $ARSS_{Min}$ based on empirically determined dependency of the packet loss rate on the $ARSS$. The experimental setup consisted of a mobile station (MS), a base station (BS) and a wired node connected to the Ethernet backbone behind the BS. The MS communicates with the wired node in a request-response (round-tip) way with a 64bytes packet every 50ms. The MS was moved at 28 different service locations. At every service location we have measured the RSS at the BS and the packet loss rate at the MS from a sample of 2 minutes of application traffic. In order to measure the effect of ARSS on the packet loss rate we have tried to minimize the effect of collisions and interference. The experiment has been conducted during the weekend, when nearby wireless networks have been very rarely used which minimized the collisions and interference. Figure 6.3 shows the dependency of the packet loss rate on the ARSS. We observe a well-expected trend that the packet loss rate decreases when the ARSS increases. This is because when the RSS is too low the wireless card can not successfully decode the packets. We also observe that the fall in the curve has some fluctuations. We explain these fluctuations with asymmetric communication. For the peak values of packet loss rate, the down-link (BS -> MS) had lower ARSS than the up-link (MS -> BS). Therefore, the "response" packet was retransmitted and eventually lost. The higher the ARSS, the lower the probability of an asymmetric communication. Therefore the fluctuation decreases when the ARSS increases. We have determined from the graphic that for ARSS values higher than -78dBm, the packet loss rate remains under 2% with only one outlier. Based on our experience [1, 3, 2, 7, 20, 21], 2% packet loss rate is sufficient for a stable link. For this reason, we choose $ARSS_{Min} = -78dBm$. For the parameter $\Delta ARSS$, we have used a value of 15dB which is in the recommended range of 10-20dB [108].

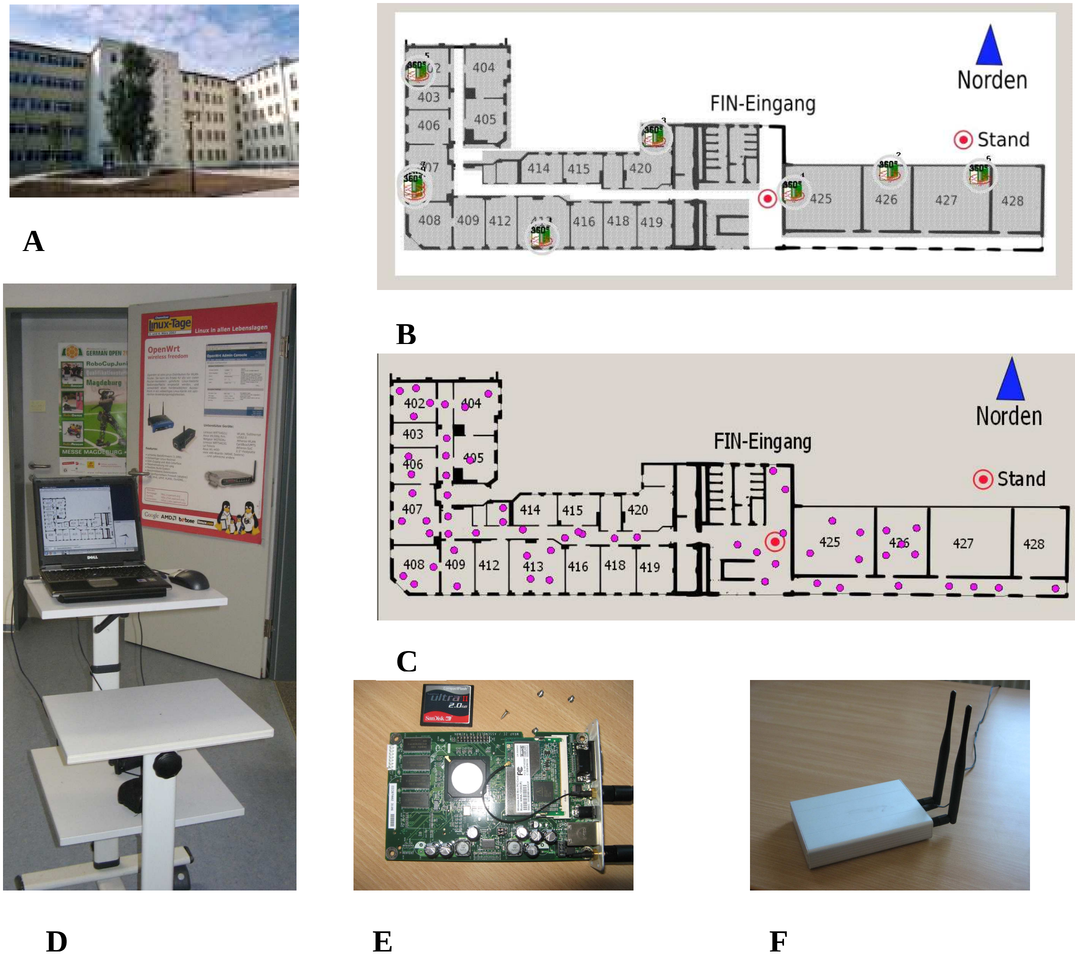


Figure 6.2.: Experimental setup for radio coverage assessment scenario 1. A: Computer science building, B: Access point-layout, C: Evaluation locations, D: Measurement station for collecting evaluation data, E F: Used access points inside and outside view.

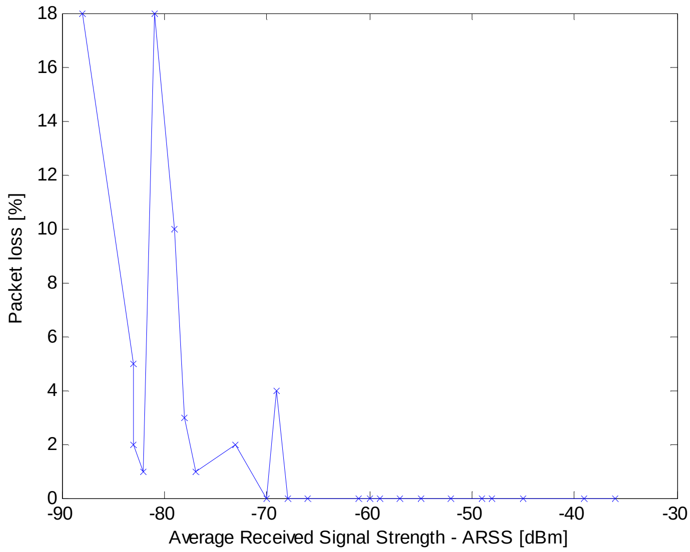


Figure 6.3.: For ARSS values higher than -78dBm, the packet loss rate remains under 2% with only one outlier

Path loss exponent	Scenario 1	Scenario 2
Office brick walls	3.18	n.a.
Office concrete walls	3.21	n.a.
Logistics hall (lightly obscured)	n.a.	2.25

Table 6.3.: Values for the model parameter "Path loss exponent" for the different scenarios and environment types after the automatic model calibration

6.3.4. Evaluation Results

After the model calibration, we obtained the following parameters for the radio propagation model (tables 6.3 and 6.4).

For scenario 1, the determined attenuation factors (path loss exponent) for the brick walls and concrete walls are almost the same. Concrete has stronger attenuation on the radio waves than bricks, but in this scenario there are more walls in the bricks area than in the concrete area, so both effects compensate.

For scenario 1, the evaluation of the assessment accuracy of our approach and the state of the art approach is shown on figure 6.4 . The results clearly show that with our approach the majority (74%) of the assessments are correct. There exist some assessments that are not correct, but these are only false positives (underestimation). In these cases the radio coverage is better than estimated. The state of the art approach has less correct

Standard deviation	Scenario 1	Scenario 2
2.4GHz	7.28	n.a.
5GHz	n.a.	6.87

Table 6.4.: Values for the model parameter “Standard deviation” for the different scenarios and frequencies after the automatic model calibration

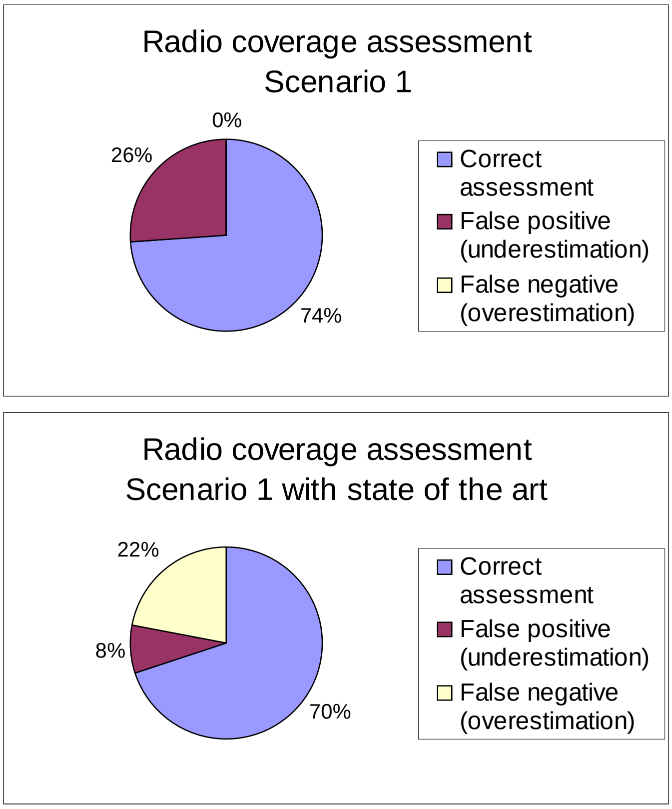


Figure 6.4.: Accuracy of radio coverage assessment in scenario 1

Infrastructure-based radio coverage assessment

Real state: Assessed state:	Failure	Error	Normal
Failure	2%	13%	3%
Error	0%	72%	10%
Normal	0%	0%	0%

Assessment with the standard model parameters

Real state: Assessed state:	Failure	Error	Normal
Failure	0%	0%	0%
Error	2%	65%	8%
Normal	0%	20%	5%

Table 6.5.: Evaluation results for radio coverage assessment in scenario 1

assessments than our approach. Moreover the false negatives of the state of the art approach are quite a high amount (almost 1/4 of all assessments).

Table 6.5 shows a breakdown of the assessment results into the possible outcomes of the evaluation as defined in table 6.1. The numbers are in percent of all evaluation locations.

Our assessment approach has correctly identified almost all errors. The rest of them have been underestimated as failures. From the fault-tolerance point of view, this means that our system initiates a recovery for all errors. *Therefore, we can conclude that the error detection is correct*. All failures have been correctly identified. The reason for this result, is that our approach calibrates the model and uses an assessment with a confidence level, based on the calibration result.

The state of the art assessment approach did not detect the errors correctly. In 20% of the evaluated service locations, errors in the real system have been identified as a normal state.

Statistics about the radio model prediction accuracy are given in table 6.7. The model prediction accuracy is the difference between the predicted and the real ARSS. A positive difference means a tend to overestimation. A negative difference means a tend to underestimation. These statistics explain the above results. The state of the art method overestimates the ARSS. Our infrastructure-based method minimize the overestimation.

For scenario 2 the evaluation of the assessment accuracy shown on figure 6.5 .

In this industrial scenario the difference between our approach and the state of the art approach is even higher. Our approach identifies the state correctly in 88% of the cases which is with 20% more than the state of the art approach. Moreover, our approach has no false negatives whereas the state of the art approach has 23% false negatives. The

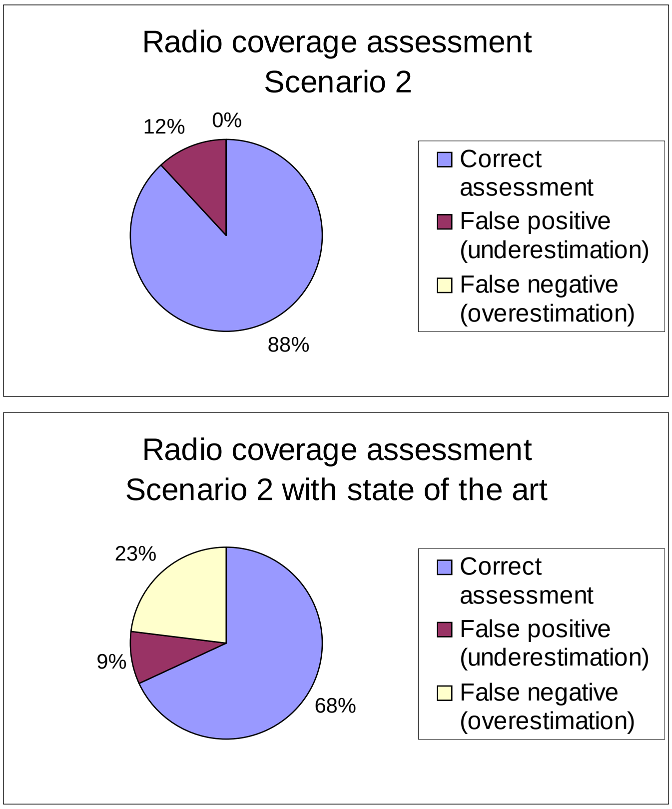


Figure 6.5.: Accuracy of radio coverage assessment in scenario 2

Assessment with our method:

Real state: Assessed state:	Failure	Error	Normal
Failure	0%	0%	0%
Error	0%	88%	12%
Normal	0%	0%	0%

Assessment with state of the art:

Real state: Asses ed state:	Failure	Error	Normal
Failure	0%	0%	0%
Error	0%	65%	9%
Normal	0%	23%	3%

Table 6.6.: Evaluation results for radio coverage assessment in scenario 2

	Scenario 1		Scenario 2	
	Mean	Standard deviation	Mean	Steve
Our method	-5	7	-1	7
State of the art	9	8	2	7

Table 6.7.: Average accuracy of the radio propagation model in all scenarios (in dB)

false positives of our approach are comparable to the false positives of the state of the art method.

Table 6.6 shows a breakdown of the results in figure 6.5 into the possible outcomes of the evaluation as defined in table 6.1. The numbers are in percent of all evaluation locations.

In scenario 2, all errors have been correctly identified as errors. There were no failures because the size of the logistics hall was rather small and there were no service locations with insufficient signal strength. 12% of the measurements have been normal state. Our assessment method has identified them as errors, but these are false positives. This is due to our approach to minimize the false negatives. Table 6.6 shows the results of the state of the art method. There are 23% false negatives: error states identified as normal states. Our method minimizes the false negatives without increasing the false positives too much. This is because of two effects: the calibration of the model minimizes the discrepancies between model and accuracy and gives information about the expected deviation. The assessment with confidence minimizes the false negatives.

6.3.5. Conclusions from the Evaluation

Our method for infrastructure-based error detection has detected all errors in the system in both scenarios.

Compared to the state of the art our method for coverage assessment is:

- More accurate: a higher amount of states is correctly assessed. This is because of our approach for model calibration (the adjustment of the model parameters to the real environment).
- It has no false negatives (overestimation). The state of the art methods often overestimate the signal strength and the state of the radio coverage. A first reason is because of the choice of the parameter. The default path loss exponent is too low. A second reason is because there is no confidence of the assessment. The underestimation and overestimation are equally probable. In contrast our approach performs an assessment with confidence which minimizes the false negatives. Our approach obtains the required amount of confidence from the model calibration.

6.4. Localization-based Error Detection

6.4.1. Purpose of the Experiment

The purpose is to evaluate whether the developed localization-based error detection approach can detect the environmental dynamics. In particular, we want to evaluate the following:

Initialization The advantage of our automatic initialization approach over the state of the art manual approaches is that it saves time and effort for collecting the training data. This is a real advantage, if it does not sacrifice the localization accuracy. Therefore, our goal is to compare the location estimation inaccuracy of our initialization approach to the inaccuracy of the manual initialization approaches.

Estimation improvement Our goal is to evaluate whether the Kalman smoothing decreases the localization inaccuracy significantly; compared to the inaccuracy of the estimation and to the inaccuracy with standard Kalman filtering.

Localization-based model calibration and error detection The purpose of our localization approach is to provide radio signal measurements for model calibration. Therefore, we want to evaluate whether, with the help of the localization, it is possible to obtain new information about the propagation environment and to detect errors.

6.4.2. Initialization

Evaluation approach Our approach is to compare the location estimation inaccuracy with an automated initialization to the location estimation inaccuracy with a manual initialization. In order to see the effect of the initialization approach on the location estimation, we performed the comparison under the same conditions: the same environment, network topology, location estimation method and evaluation data.

The initial situation is that the measurements among the base stations can detect the environmental dynamics, i.e. the base stations are on the same plane with the service area. We deploy the WMN according to this criteria. The base stations perform radio signal strength measurements among each other and deliver the information to the eWST tool. The tool performs radio model calibration based on the positions of the base stations and the signal strength measurements (as defined in section 4.3). On the basis of the calibrated model the eWST tool generates the training data (as defined in section 4.4.3). Then we collect evaluation data for the location estimation. On selected *evaluation locations* in the service area we measure the ARSS from the base stations. Then we perform location estimation based on the training data and on the ARSS measurements at the evaluation locations. The location estimation accuracy is the difference between the real evaluation locations and the estimated locations.

Then we perform an initialization with the manual method. At selected training locations within the service area we measure the ARSS from the base stations. The training locations are different from the evaluation locations. Then we use the same evaluation data and the same location estimation method to derive the localization inaccuracy.

We compare the localization inaccuracy of the automatic initialization to the localization inaccuracy of the manual initialization. If the difference is not significant, we can conclude that our initialization approach is successful. This would mean that the advantage of the automatic initialization does not sacrifice the localization accuracy.

Implementation of the evaluation approach We have implemented this evaluation approach in scenario 1 (University of Magdeburg) and scenario 2 (Galileo logistics hall). For a description of the scenarios see section 6.3.3. Figure 6.6 shows the Galileo logistics hall and figure 6.7 shows part of our experimental setup in this hall. We have used the location estimation method defined in section 4.4.4.

In both scenarios the training data for the manual initialization was collected at fixed service locations. At every training location we measured the ARSS by using a laptop with a PCMCIA WLAN card (see figure 6.2). The training data has been collected for 60 seconds per training location. At each training location the mobile station has been turned in all directions during the measurement time in order to measure the effects of the directional antenna in the ARSS values. In scenario 1 we collected 35 training locations and it took 90 minutes. In scenario 2 we collected 34 training locations and it took 68

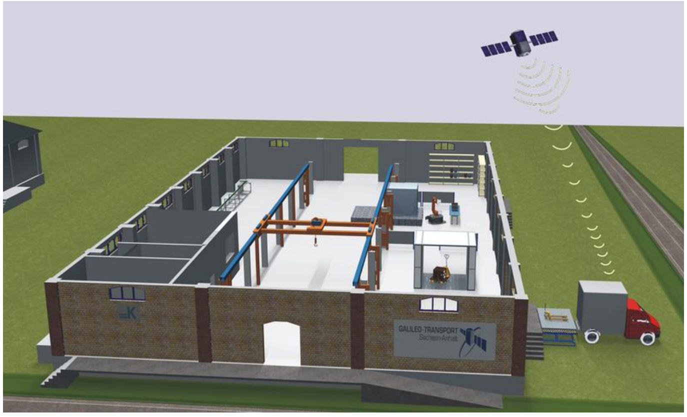


Figure 6.6.: Galileo-Testfeld Sachsen-Anhalt, logistics lab [33], Magdeburg, Germany. Image source: "University of Magdeburg"

Figure 6.7.: Experimental setup in the Galileo logistics lab [33]

minutes.

The training data for the automatic initialization has been generated from the radio propagation model. For scenario 1 we have generated 10000 training points on a 80x30cm grid. For scenario 2 we generated less training points (260 on a 2x2m grid), since we noticed that a granularity of less than 2 meters has no significant effect on the ARSS.

The main difference between the two scenarios (besides environment types and the frequency) was the collection of evaluation data. In scenario 1 we have collected evaluation data with a static profile. In scenario 2 we have collected evaluation data with a mobile profile. A mobile profile means that the evaluation data was collected while the node was moving. The mobile evaluation profile brings two important influencing factors. The first one is that for each location we have only a few (2-3) measurements - we are not able to make an average over a larger measurement sample. The second more influencing factor is that the wireless card had a strong unidirectional profile (it was a PCMCIA card with an embedded antenna). During the measurement, because the station was on the move, we were not able to turn it in all directions and measure the directional effects. For this reason we expect a lower location estimation accuracy in the second scenario.

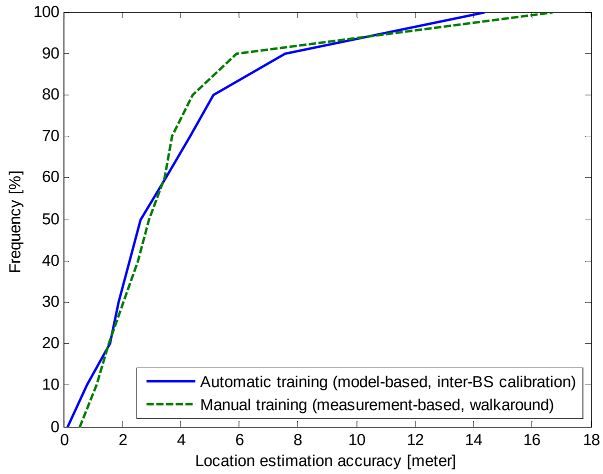
In scenario 1 we reused the evaluation data from infrastructure-based error detection (63 evaluation locations). In scenario 2 we have collected the evaluation data from a mobile station which moved for about 3 minutes in the service area. During the movement the position was recorded around every 1-2 seconds.

Evaluation results Figure 6.8 shows the results for scenario 1. Our automatic initialization method achieves nearly the same location estimation accuracy as the traditional methods with manual measurements. The clear advantage of our method is that it does not need any manual effort. The manual training took 90 minutes.

The inaccuracies of the automatic method stem from the inaccuracies of the prediction model. The inaccuracies of the method with manual method stem from the fact that the training-positions and the evaluation-positions differ. This is not the case for the automatic method because it can generate training samples with any density. The results show that the effects of both inaccuracy sources lead to nearly the same localization inaccuracy. The manual method has a slightly lower inaccuracy. However, in large plants, it takes lots of time and money and it has an aging problem: when the environment changes the training is no longer accurate. The automatic initialization is much more beneficial for industrial applications.

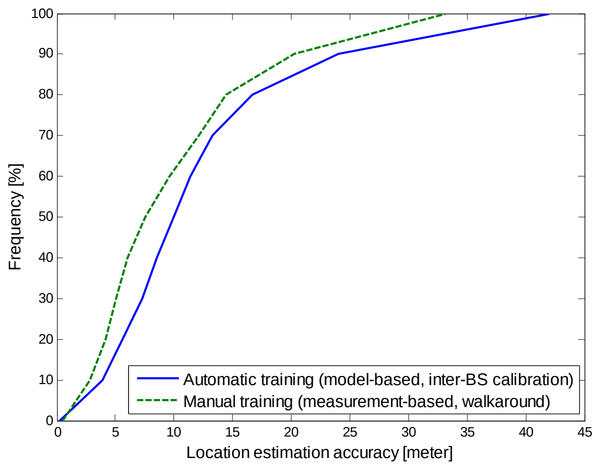
In scenario 2 we observe similar differences between the automatic and the manual approach. The mean inaccuracy with the automatic initialization is about 20% higher than the mean inaccuracy with the manual method. However, the automatic method requires no time for training vs. 68 minutes for the manual method.

The location estimation inaccuracy in scenario 2 is higher than the inaccuracy in scenario 1. This observation is for both the automatic and the manual initialization methods. The reason is that in scenario 2 the evaluation profile was mobile and the directional antenna profile of the mobile station was not taken into consideration. In most directions the directional antenna results in a lower ARSS than the ARSS in the training data. In order to support this explanation we performed an additional test. We generated the training data with a higher path loss exponent than the one obtained by the calibration (we used a value $PLE = 4$). A higher PLE means more attenuation and lower ARSS at the service locations. With this training data we obtained a lower inaccuracy than the inaccuracy of the manual method (the mean was 8.5 meters and the standard deviation was 4.6 meters). It seems that the directional orientation of the mobile station has resulted in a radio signal strength which is lower than the predicted one and is reproduced better by a higher path loss exponent.



Initialization method	Accuracy mean [m]	Accuracy std [m]	Training time
Automatic (inter-BS)	3.7	3.4	-
Manual	3.1	2.6	90min

Figure 6.8.: Location estimation accuracy as a function of the initialization method for scenario 1



Training method	Accuracy mean [m]	Accuracy std [m]	Training time
Automatic (inter-BS)	12	8.2	-
Manual	9.7	7	68min

Figure 6.9.: Location estimation accuracy as a function of the initialization method for scenario 2

Conclusions from the evaluation Our automatic initialization method saves the time and effort for training. It results in an location estimation inaccuracy which is about 20% higher than the respective inaccuracy with the manual method. In the next two experiments we will consider what is the effect of this inaccuracy on the estimation improvement, model calibration and error detection.

In this experiment, we made another important observation. When a mobile evaluation profile is used and the antenna of the mobile station is directional, the location estimation accuracy has a significantly higher inaccuracy as compared to the case of static evaluation profile. This is important since the purpose of localization in the context of this thesis is to collect information from mobile stations during their normal operation. In the general case, this means that they will move and will have a situation similar to the mobile evaluation profile. For this reason, we will take a closer look at the mobile evaluation profile in the next two experiments. First, we will evaluate the ability of Kalman smoothing to improve the location estimation of the mobile profiles. Secondly, we will evaluate the ability of our localization method to give new information about the environment and the ability of our localization-based error detection method to detect the environmental dynamics.

6.4.3. Estimation Improvement

Evaluation approach Our evaluation approach is to compare the accuracy of the location estimation to the accuracy of the estimation improvement. The proposed estimation improvement uses the location estimation as a basis and performs Kalman smoothing to improve the accuracy (section 4.4.5). We also compare the improvement of Kalman smoothing to the improvement of the traditionally used Kalman filtering. The estimation improvement is useful for measurement time sequences. Therefore, only the mobile evaluation profile will be used. There are several factors, affecting the estimation improvement: the location estimation accuracy, the movement profile of the mobile station and the parameters of the Kalman smoother.

Implementation of the evaluation approach We have implemented the evaluation approach in two scenarios under different environments and conditions (table 6.8).

In scenario 1 (University of Magdeburg), we have selected conditions which are most favorable for the localization accuracy. The training data has been collected manually and omnidirectional antenna profile was used. In this implementation, the network was different from the one used for evaluation in this scenario. The reason is that we wanted to see the effect of more base stations on the localization. We have used 9 base stations and a half of the area of the 4th floor (35x27m). Figure 6.10A shows the locations of the base stations and figure 6.10B shows the movement profile used for evaluation. These conditions promise a better location estimation. The movement had a slow speed

	Scenario 1 (University of Magdeburg)	Scenario 2 (Galileo logistics lab)
Initialization method	Manual training	Automatic
Antenna profile	Omnidirectional	Directional
Movement profile	Constant speed, almost no curves	Constant speed, few curves
Assumed $Speed_{max}$, $[m/s]$	1	1.5
Assumed$LocationInnaccuracy_{std}$, $[m]$	4	6
Process noise $var(w_x), var(w_y)$, $[m/s]^2$	0.33	0.75
Measurement noise $var(z_x), var(z_y)$, $[m^2]$	22.63	50.91

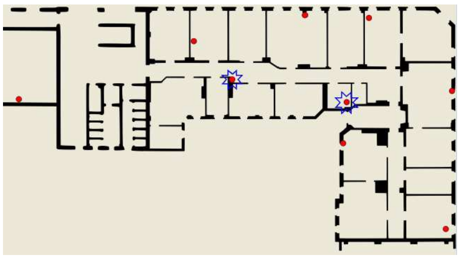
Table 6.8.: Evaluation scenarios and parameters for the estimation improvement

($Speed_{max} = 1m/s$) along the corridors of the building which had only one curve. During the movement we recorded the position of the mobile station every $T = 1sec$ for evaluation purposes.

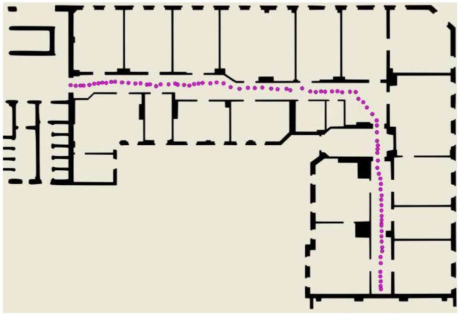
In scenario 2, we have used the same experimental setup as for the evaluation of the localization initialization in the previous section: automatic training data, directional antenna profile, slightly higher speed ($Speed_{max} = 1,5m/s$) and several curves. Because of the directional antenna and the automatic training, this scenario is a worst case.

The Kalman filter noise parameter values are significant for the estimation improvement. Therefore, we determined these values in a way, based on information which will be available in a real application scenario in automation: the maximum speed and the standard deviation of the location estimation inaccuracy. Then we used equations 4.34 and 4.39 for this purpose. The used parameter values are shown in table 6.8.

Evaluation results Figure 6.11 shows the results of the experiments in scenario 1. It shows the movement profile of the mobile station, the location estimation, the estimation improvement with filtering and with smoothing and a table with statistics. The statistics clearly show that the estimation improvement with smoothing significantly decreases the localization inaccuracy. The mean is decreased by 36%, the standard deviation by 59% and the *maximum is decreased by 79%*. Our estimation improvement approach with smoothing is also better than the traditional approaches that use filtering. The traditional approach also significantly decreases the inaccuracy (20%, 28% and 70% for the mean, standard deviation and the maximum respectively). However, the smoothing approach decreases the inaccuracy more than the filtering approach. This can also be observed on the plotted movement profiles on figure 6.11. The estimation improvement with smoothing fits the real movement profile better than the estimation improvement with filtering.

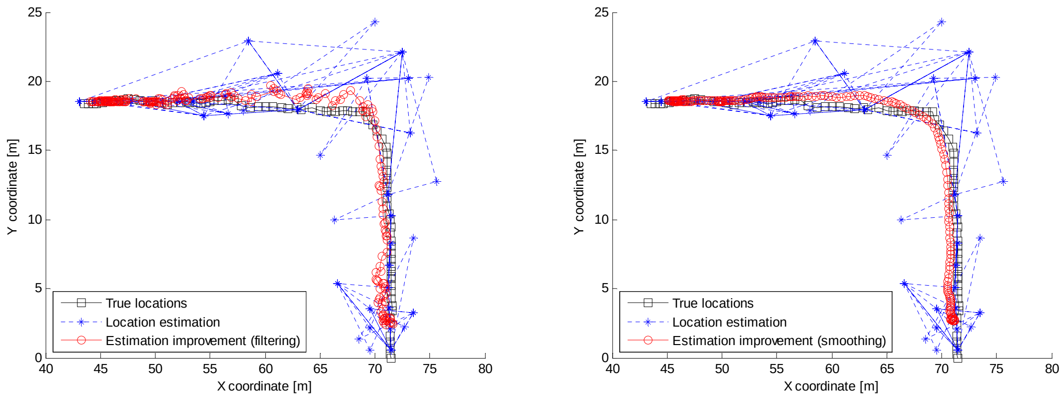


A) Locations of the base stations



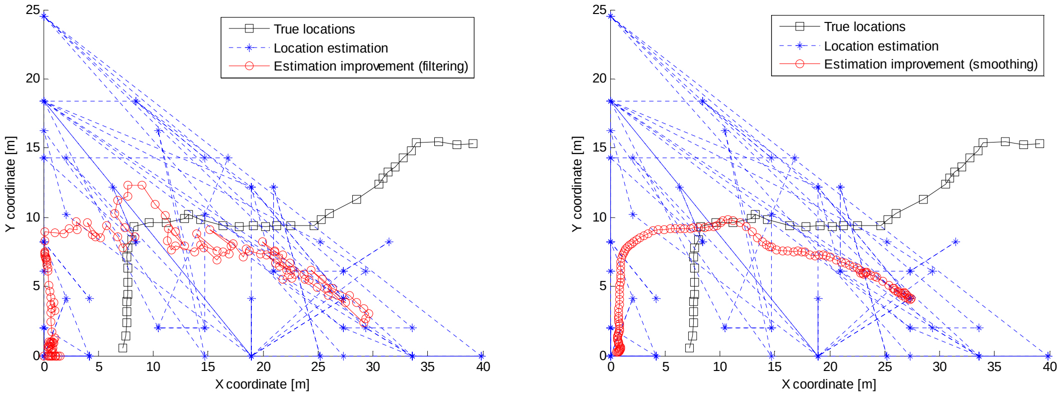
B) Movement profile for the evaluation

Figure 6.10.: Evaluation scenario "University of Magdeburg" for estimation improvement. The source of the images is [121].



Localization inaccuracy [meter]	Mean	Standard deviation	Minimum	Maximum
Location estimation	3.9	3.2	0.2	29.6
Estimation improvement (Kalman filter)	3.1	2.3	0.05	8.5
Estimation improvement (Kalman smoother)	2.5	1.3	0.03	6.2

Figure 6.11.: Estimation improvement results for scenario 1



Localization inaccuracy [meter]	Mean	Standard deviation	Minimum	Maximum
Location estimation	10.9	6.2	2.8	40.2
Estimation improvement (Kalman filter)	9.9	2.4	6.2	16.9
Estimation improvement (Kalman smoother)	8.3	2.7	5.3	16.9

Figure 6.12.: Estimation improvement results for scenario 2

Figure 6.12 shows the results for scenario 2 in a way that is analogous to the results for scenario 1. A similar trend is observed in these results. The estimation improvement with smoothing decreases the inaccuracy of the location estimation. It decreases it more than the traditional approaches with filtering. Similar to scenario 1, in this scenario the most significant decrease in inaccuracy is in the standard deviation (56%) and in the maximum value (58%). The decrease in the mean inaccuracy is also significant (by 24%).

The plots of the movement profiles show the effects of different conditions on localization accuracy. In “good” conditions the movement profile is almost perfectly tracked (figure 6.11). In “worse” conditions, the smoothing has a significant improvement over the location estimation, but the movement profile is less accurately tracked.

Conclusions from the evaluation Both evaluation scenarios have shown that our approach for estimation improvement with Kalman smoothing significantly decreases the inaccuracy of the location estimation. Our approach is better than traditional improvement approaches which use Kalman filtering.

In addition, the experiments confirm our method for setting the Kalman filter noise parameters. The results show that with simple assumptions about the system (the stations speed and the location estimation accuracy) and with an adequate way of determining the parameters, one can get a significant improvement.

6.4.4. Localization-based Model Calibration and Error Detection

The localization approach has been developed especially for the situation, in which the infrastructure-based measurements can not detect the environmental dynamics (e.g. the base stations are at the ceiling, the obstacles rise from the ground and do not reach the ceiling). *Therefore, it is of essential importance to evaluate how the localization method helps in detecting the changes in the propagation environment.* We use the following evaluation approach.

Evaluation approach We assume that in a given moment in the past (e.g. the previous day) the propagation environment has been other than the actual propagation environment. The propagation environment in the past is the initial propagation environment. The actual propagation environment is the environment which we have at the moment in our evaluation (in this case the logistics hall Galileo in scenario 2).

The propagation environment can be quantified by the parameters of the radio propagation model (n, σ) which are the path loss exponent n and the shadowing deviation (see section 4.2). Let (n_i, σ_i) are the parameters of the initial propagation model. It does not matter how these model parameters have been derived (manual measurements, automatic measurements, etc.). What is important is the assumption that in the past we had an initial environment (estimated by the model-parameters (n_i, σ_i)) which is different from the actual propagation environment (estimated by the model parameters (n_a, σ_a)).

Firstly, we perform the initialization step of the localization based on the initial propagation model. The initialization includes the generation of training data as defined in section 4.4.3. Then we assume that the propagation environment has changed (due to some dynamics) from the initial propagation environment to the actual propagation environment. The measurements among the base stations can not detect this change. We implement this by disabling the inter-BS measurements. Then the only way to detect the "change" in the environment is by using localization-based measurements. For this purpose we perform localization as defined in section 4.4. However, the special fact of this localization is that the training data has been generated by using an *outdated* propagation model. Our goal is to evaluate how the information, gained from the localization (based on outdated training data), can help us to detect the "change" in the environment. Detecting the "change" of the environment in this experiment means to *determine* actual model parameters $(\widehat{n_a}, \widehat{\sigma_a})$ which are a *good estimate* of the real actual model parameters (n_a, σ_a). The actual model parameters $(\widehat{n_a}, \widehat{\sigma_a})$ are *determined* by the radio model calibration (section 4.3) by using radio signal measurements, provided by the localization (section 4.4). A *good estimate* means that the error detection with the model parameters $(\widehat{n_a}, \widehat{\sigma_a})$ is at least as good as the the error detection with the real actual model parameters (n_a, σ_a).

Implementation of the evaluation approach We used scenario 2 for this evaluation. It is an industrial scenario and the localization results in this scenario had higher inaccuracies than in scenario 1. If our approach is successful with higher inaccuracies, then we can expect that it will be also successful with lower localization inaccuracies.

We have used different values for the parameters of the initial propagation environment. For the path loss exponent, we used values in the range $[1.5...4]$ which describes a wide range of environments [108].

For every initial environment parameters, we used the measurement time sequence which was used in the evaluation of the localization in this scenario so far. This sequence was localized and localization-based ARSS measurements have been derived, as described in section 4.4. With the measurement data used as an input, the model calibration method determined the path loss exponent and the shadowing factor of the actual propagation environment. For every initial environmental parameters, this process was repeated until the difference in the estimated path loss exponent was less than 0.1. In this way, we evaluated the convergence of our method in determining the actual environmental parameters. With the converged model parameters we performed radio coverage assessment in the actual environment in order to evaluate the localization-based error detection. For the assessment, we used the same evaluation data as in section 6.3 which enabled us to compare the localization-based assessment to infrastructure-based assessment and the state of the art approach.

Evaluation results Figure 6.13 shows the convergence results for the path loss exponent. At iteration 1 the path loss exponent has the value for the initial environment from the range $[1.5...4]$. Every iteration shows the change in the path loss exponent from an initial value to a new value. This change is due to the model calibration from localization-based measurements. For instance, from the initial value 1.5 we obtained a value 2.37. From 2.37, we obtained 2.49 and from 2.49 we obtained 2.49 once again. Similarly for the other initial values. The figure clearly shows that after three iterations the path loss exponent *converges to a stable value* (2.49), independently from the initial value $[1.5...4]$. In addition the stable value is very close to the baseline value for the path loss exponent. The baseline value was determined by the model calibration from infrastructure-based measurements (section 6.3). If we use training with a manual site survey we derive model parameters 2.25/6.89.

Table 6.9 shows the details of the parameter convergence. We see that the shadowing deviation also converges to a stable value between 9 and 10. When the initial path loss exponents are too small or too large, the shadowing deviation is greater than 11. When the initial path loss values converge to the final value 2.49, the values for shadowing deviation also converge to a stable value.

This convergence can be explained in the following way. When the initial path loss

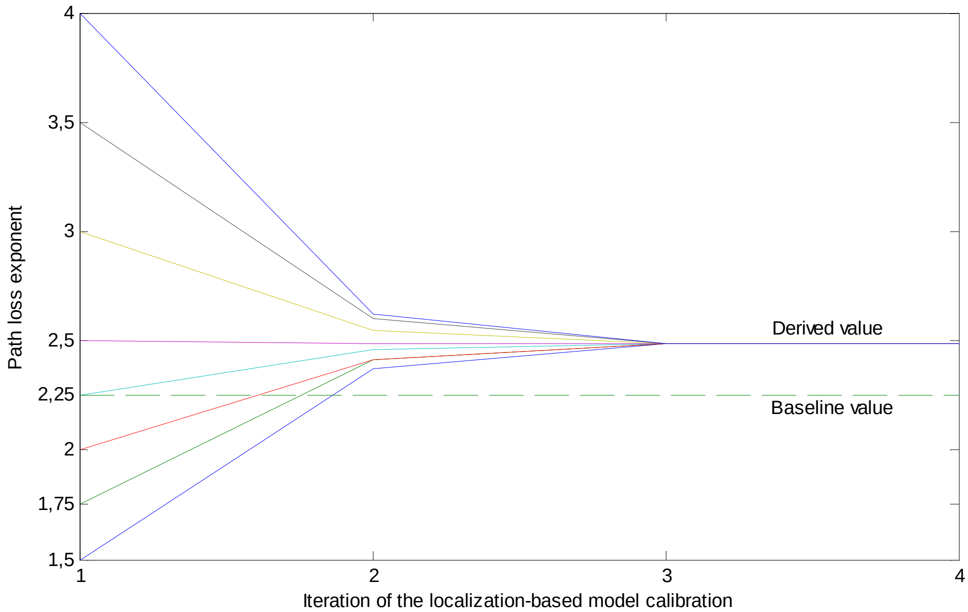


Figure 6.13.: The path loss exponent converges to a stable value close to the baseline

Initial model parameters		Derived model parameters	
Path loss exponent	Shadowing deviation	Path loss exponent	Shadowing deviation
1.5	0	2.37	11.54
1.75	0	2.41	11.15
2	0	2.41	9.42
2.37	0	2.49	10.06
2.41	0	2.49	9.53
2.46	0	2.49	9.66
2.49	0	2.49	9.73
2.5	0	2.49	9.62
2.55	0	2.49	9.38
2.56	0	2.50	9.61
2.6	0	2.49	9.52
2.62	0	2.50	9.45
3	0	2.55	9.3
3.5	0	2.6	9.86
4	0	2.62	10.14

Table 6.9.: The derived model parameters from different initial environment (shadowing factor not used for training)

exponent is far from the stable value the localization has a higher inaccuracy. This leads to a higher shadowing deviation (like table 6.9 shows), but the calculated path loss exponent moves in the right direction. The analysis in section 4.5 gives the explanation for this behavior and this experiment has proved our analysis.

Based on the results (figure 6.13 and table 6.9), we can conclude that the location-based model calibration converges to a stable value of the model parameters, *regardless of the initial environment*. In this case, the model parameters converged to (2.49/9.73). This means that the method can detect the environmental dynamics.

Now, an important question is how good can these converged model parameters detect errors in the actual environment. To answer this question, we performed a radio coverage assessment with the derived model parameters.

Table 6.10 shows the results of the localization-based assessment. In 74% of all evaluation locations, the service state has been correctly assessed as an error. There are some cases of errors, identified as failures. However, as we previously discussed, this case is not critical for the fault-tolerance approach. The important fact is that if an error exists in the system, then our method detects it and initiates a system recovery. As a whole, the localization-based assessment has more false positives (underestimations) than the infrastructure-based assessment. This can be explained by the fact that the localization-based measurements provide the mobile stations view on the radio coverage. As a result of directional antennas, the estimated path loss exponent of the environment is higher, than the PLE in the case of infrastructure-based measurements. There were no false negatives. This assessment is also better than the state of the art assessment.

We also evaluated the case when the shadowing factor was used for the initialization of the localization (table 6.11). We observed that in this case, the convergence was not as good as in the previous case. The derived value for the path loss exponent tends to go over 2.5 and the value for the shadowing deviation tends to go over 11 which is a too high value. This behavior occurs because when the shadowing factor is used, the training data becomes more inhomogeneous. This leads to a larger variation in the localization inaccuracy and to a larger variation in the derived measurements. This leads to a larger shadowing deviation. For this reason, or proposal is to perform the initialization of the localization without the shadowing factor.

Conclusions from the evaluation Our method for localization-based error detection is successful. It successfully detected the dynamics of the environment. Regardless of the model parameters of the initial environment before the change, our method derived the model of the environment after the change. This is an iterative process which converged to a stable value. In the case when infrastructure-based measurements can not detect the environmental dynamics, the localization-based approach is a more promising alternative for error detection.

It is possible to combine both error detection methods. If the infrastructure-based

Infrastructure-based assessment

Real state: Assessed state:	Failure	Error	Normal
Failure	0%	0%	0%
Error	0%	88%	12%
Normal	0%	0%	0%

Localization-based assessment

Real state: Assessed state:	Failure	Error	Normal
Failure	0%	14%	0%
Error	0%	74%	12%
Normal	0%	0%	0%

State of the art assessment

Real state: Asses ed state:	Failure	Error	Normal
Failure	0%	0%	0%
Error	0%	65%	9%
Normal	0%	23%	3%

Table 6.10.: Evaluation results for the localization-based error detection in scenario 2

Initial model parameters		Derived model parameters	
Path loss exponent	Shadowing deviation	Path loss exponent	Shadowing deviation
1.75	6	2.56	10.28
2	6	2.56	10.17
2.25	6.87	2.46	9.6
2.37	11.54	2.55	11.10
2.43	9.52	2.50	10.39
2.56	10.28	2.54	10.92
2.62	10.14	2.56	11.57

Table 6.11.: The derived model parameters from different initial environment (shadowing factor used for training)

can detect the environment, it can be used as a good basis for the initialization of the localization. Then the localization-based method can provide the view of the mobile stations on radio coverage.

6.4.5. Conclusions from the Evaluation

Our method for initialization saves time and effort for generating the training data. Our method for estimation improvement reduces significantly the localization inaccuracy. Our location-based error detection method detects changes in the environment in a stable and reliable way and provides a mobile station's view on the radio coverage. These significantly improve the error detection.

6.5. Automatic Base Station Planning for System Recovery

The intensive evaluations in the previous two sections with a real network in different environments have shown that our automatically calibrated radio propagation model is able to accurately assess the real environment in a reliable way. Therefore, we can conclude that if we perform the recovery in the model, then the same reconfiguration will also be a recovery in the real network. Then question remains: given a system model with errors, what could be the minimum set of reconfiguration actions that can remove the errors from the system? For this question, we have developed the automatic base station planning algorithm. In this section, we will present evaluation of this algorithm.

Evaluation approach and implementation We evaluate the algorithm according to the following important evaluation criteria:

- Fault-tolerance: this shows the algorithm's ability to generate a network configuration that satisfies the fault-tolerance coverage requirements.
- Termination: this shows the number of iterations the algorithm needs to complete and the running time.
- Minimality: this shows the ability of the algorithm to use minimum number of base stations.

We performed a model-based evaluation of the algorithm. We generated different inputs to the algorithm, then executed the algorithm and observed the evaluation criteria. As an input of the algorithm, we used a service area with various sizes; typical for a production environment (see table 6.12 for the parameter values). The service locations comprise of the entire floor. The candidate sites comprise of the entire ceiling. We also varied

Parameter	Values
Transmit power P_{tx} [dBm]	20
Required receive power P_{min} [dBm]	-78
Path loss exponent	3
Area size (X/Y) [meters]	(50/50),(100/100),...,(300/300)
Shadowing deviation σ [dB]	5,6,7,8,9,10

Table 6.12.: Evaluation parameters

the attenuation of the propagation environment. For the radio connectivity model, we used the log-normal shadowing propagation model [108] which is used for radio coverage assessment (see section 4.2. The path loss exponent has been fixed in these experiments. The shadowing factor X_σ models the inhomogeneity of the propagation environment and it has been varied in these experiments. The other parameters of the propagation model are fixed. To determine the connectivity, we used our threshold-based link state model. The base station planning algorithm has been implemented in Matlab (about 600 lines of code). The algorithm has been tested on all the combinations of input parameters (area size and shadowing deviation) which make a total of 36 executions. At the end of each algorithm execution, we performed a requirements test. We tested whether the radio coverage and the connectivity were in normal (redundant) state.

Results for fault-tolerance With all the inputs, the algorithm has generated a network topology in which the radio coverage and the connectivity were in the normal (redundant) state, as defined in section 3. An example graph of the network topology, generated by the algorithm for area size 200/200m and shadowing deviation 8 is shown on figure 6.14. The related work algorithms [36, 120] generated topologies which are not fault-tolerant. Their topologies optimized the network throughput, but the backbone network war not biconnected (see figure 3 in [36], and figure 4 in [120]). Figure 6.14 clearly shows the effect of the shadowing (inhomogeneous environment) on the base station planning. Because of the shadowing, some links are shorter than others and in some areas, more base stations are needed to provide coverage.

Results for termination, minimality and running time Figure 6.15 shows the measured termination property of the algorithm within the performed evaluation. The figure shows the cumulative termination, i.e. the percentage of the algorithm executions that have terminated *up to* some number of iterations. 30% of the algorithm executions generated a correct fault-tolerant solution directly after the first iteration. This means that in these cases, the graph consolidation step was not performed at all. These were the cases when the area sizes were smaller (50/50m and 100/100m). 80% of the algorithm executions generated a correct fault-tolerant topology after the second iteration. This

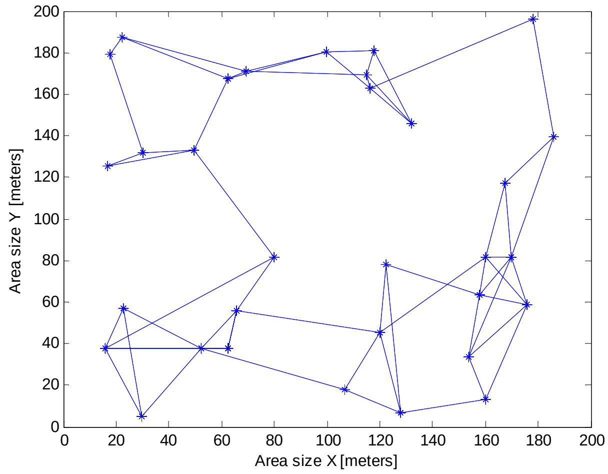


Figure 6.14.: Example fault-tolerant (biconnected) topology produced by the algorithm

means that only two optimizations and one graph consolidation were needed. The algorithm needed a maximum four iterations to complete all the inputs.

90% of the base stations were selected at the first algorithm iteration. This means that 90% were selected according to the global optimization function and were optimally placed. The remaining 10% of the base stations were selected during the subsequent algorithm iterations in order to ensure the biconnectivity of the backbone. Figure 6.16 shows the result after the first iteration for area size 150/150m and shadowing deviation 7. In the middle of the graph (around coordinates 65/44), a base station exists, whose removal would disconnect the network. In the next iteration the algorithm corrected this by inserting one base station in proximity of the first one (see figure 6.17).

For the total 36 executions, the algorithm needed about 25 minutes to complete on a laptop with a dual core 2.5GHz processor and 3GB operating memory. This means that the average running time was 42 seconds. As a comparison, a related work algorithm in [120] needed 22 hours for a 58-node scenario because of the intractability of the approach. This means that for the purpose of the system recovery, our algorithm has an acceptable running time.

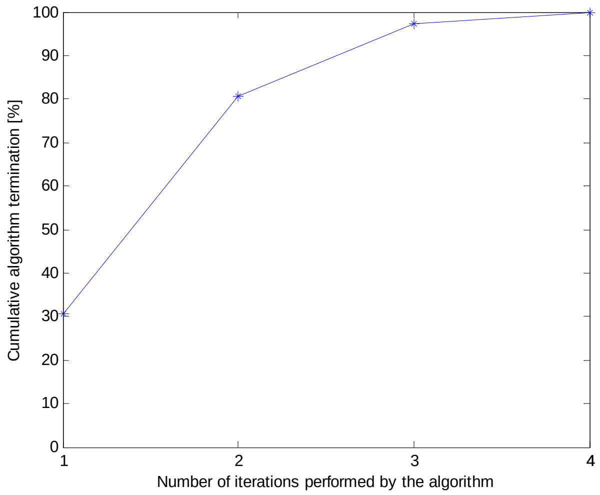


Figure 6.15.: Algorithm termination: 80% of all algorithm executions terminated after 2 iterations. The algorithm needed a maximum of 4 iterations to complete.

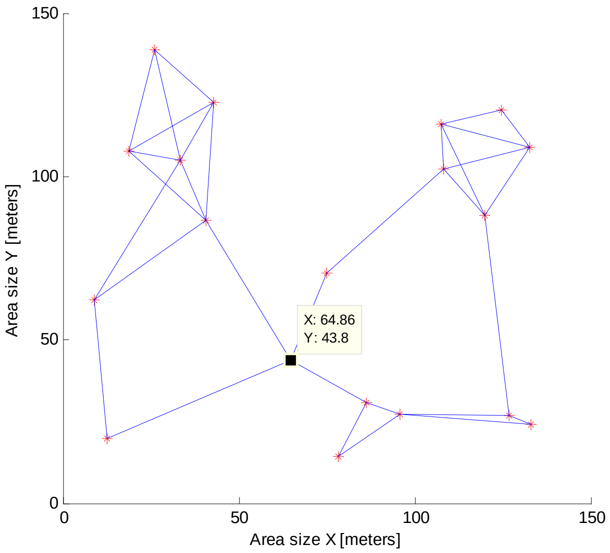


Figure 6.16.: Example network topology after the first algorithm iteration

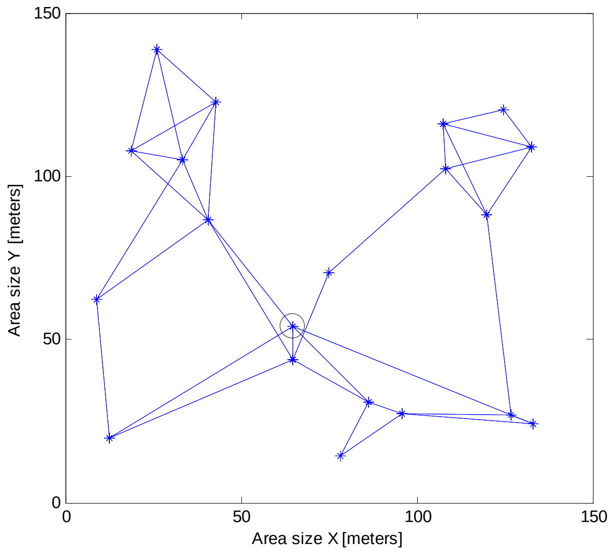


Figure 6.17.: Example network topology after the second algorithm iteration. Only one additional base station results in a biconnected topology.

7. Conclusions and Outlook

Conclusions Wireless Mesh Networks open many new possibilities for industrial automation scenarios. The lack of a wired backbone and self-organizing topology enables a flexible reconfiguration, extension, reduction and relocation of the network. These advantages are especially important in the emerging Reconfigurable Manufacturing Systems. In these systems, the production process and the factory layout are reconfigured at the system level for meeting the demands of a new market. This means relocating, extending or reducing production lines and logistics systems. A wireless network with a flexible infrastructure, like the mesh networks, promises a more detailed and up-to-date supervision and diagnosis, more flexible control and improved scalability. However, using wireless communications in these applications and environments pose some tough challenges to the non-functional properties of the communication: availability, security, and real-time [101]. One of the main challenges is that the dynamic propagation environment negatively affects the basic network services radio coverage and the connectivity.

In this dissertation, we developed a new approach for guaranteeing the availability of the services radio coverage and connectivity in dynamic propagation environments. Our approach is to apply fault-tolerance for avoiding service failures in the presence of environmental dynamics. Differing from the existing methods, we use reconfigurable redundancy of the services. As the factory-layout changes for adapting to a new market, our method changes the redundancy of services for adapting to the new propagation environment. Redundancy in the radio coverage is radio signal strength reserve within the service area. Redundancy in the connectivity is the existence of an alternative network path (biconnectivity). We define the loss of service redundancy at runtime as an error. Our approach avoids service failures by performing error detection and system recovery before the environmental dynamics leads to failure. Our system performs automatic error detection during the normal service delivery. The system recovery restores the redundancy of the services. For the application of this fault-tolerance approach in the specific context, we developed new methods for error detection and system recovery.

Our major challenge was to detect, at runtime, the effect of environmental dynamics on the radio coverage in space. Monitoring is hardly possible since there is no communication endpoint at every position in the service area. Our approach is to perform a model-based assessment for this purpose. The key innovation of this model is that it automatically calibrates to the real environment. We developed a new method for automatic radio model calibration which is a fundamental function in our system.

This function uses radio signal strength measurements from the network for adjusting the model parameters to the real environment. The model detects the environmental dynamics. If an error in the model occurs, then this is also an error in reality. The system recovery uses the model for predicting the effect of the possible network reconfigurations on the services. If a reconfiguration in the model restores the redundancy of the services, then it will also have the same effect in reality.

We developed two approaches for automatic radio signal strength measurement for the purpose of model calibration: infrastructure-based measurement and localization-based measurement. The infrastructure-based approach performs measurements among the base stations in the network. The idea is that the environmental dynamics have a noticeable effect on the measured signal strength among the base stations. Since the positions of the base stations are known, these measurements can be used for model calibration. For the case when the base stations cannot detect the environmental dynamics (e.g. base stations on the ceiling), we developed the localization-based approach which uses measurements from the mobile stations. For obtaining position information from these measurements, we developed a new localization method. This method automatically determines the positions of the mobile stations. The localization method is specifically tailored to model calibration: it performs a calibration-specific estimation improvement and inaccuracy-aware interpretation of the localization results. The interesting property of this approach is that there is a mutual dependency between radio model calibration and localization. The localization uses the model for initialization of the training data. The model calibration uses the localization results for adjusting the model parameters to the real environment. We have shown analytically and experimentally that this dependency is feasible and that it can be successfully used for detecting the environmental dynamics.

When the environmental dynamics is detected, the system recovery adds base stations to the network for restoring the redundancy of the services. But firstly, it has to be decided what the minimum number of base stations would be (and respectively their positions) which will restore the redundancy. For this purpose, we developed a new base station planning algorithm which takes the required decision and proposes reconfiguration instructions. Since the underlying optimization problem is NP complete, our algorithm is a trade-off between minimum base stations and minimum running time. The operating staff performs the network reconfiguration which restores the redundancy of the services.

We have prototypically implemented our concepts and evaluated them in different environments, including industrial. The evaluations have shown that the developed error detection methods can successfully detect errors in the services. The evaluation of the localization-based error detection showed that regardless of the initial environment before the change, our method derived the model-parameters of the environment after the change and converged to a stable state. Therefore, we can conclude that our approach successfully detects the environmental dynamics. In our evaluations, the base station planning algorithm produced network configurations with services redundancy in acceptable running time and minimal number of base stations.

Deployment of radio coverage and connectivity Up to now, we did not consider the question of initial deployment of the wireless mesh network and the services. The existing approaches require extensive measurements in the environment, expert decisions and trial installation of base stations. This can be an iterative process with an ample of trial and error. The developed concepts for radio model calibration and base station planning can be used for the deployment of the services radio coverage and connectivity. Appendix A defines a systematic approach for network deployment which uses the proposed concepts in order to minimize the time and the effort for the deployment.

Ongoing and future research The ongoing and future research includes the integration of the developed concept in systems for higher-layer end-to-end guarantees and the improvements of individual parts from the concept.

Our concept contributes to physical layer availability in a joined research for dependable end-to-end communication in wireless mesh networks within our working group. The thesis work [71] provided the methods for end-to-end throughput guarantees for the backbone of a wireless mesh network. The ongoing work [16, 17] develops concepts for end-to-end quality of service guarantees (throughput, packet loss, latency) in the whole mesh network including the mobile stations. The basic idea is to perform admission control on the per-flow end-to-end medium time. This approach requires methods for monitoring the currently available and used network resources [93, 92, 91] as well as methods for fast link failure detection [87]. For guaranteeing the availability of the radio coverage and the connectivity, these scientific works use the fault-tolerance approach presented in this thesis.

The proposed concepts for guaranteeing the availability of radio coverage are used in the currently ongoing European research project Flexware. The project develops an infrastructure-WLAN based system for factory wide real-time communication [113], including aspects of resource management, admission control, scheduling, MAC layer communication, clock synchronization and localization. Currently the implementation and evaluation phases of the project are running.

Although the present concept guarantees the availability of radio coverage and connectivity, there is still room for improvement. The link state model can be improved. The idea is to not only use a radio signal strength threshold, but to also use various monitoring information like data rate, MAC layer retransmission counters, etc. The idea is to apply a data mining based approach for predicting the link state from various monitoring information [86, 87].

List of Figures

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A. Deployment of Radio Coverage and Connectivity

In this section we describe an approach for deployment of radio coverage and connectivity. The method is described in algorithm A.1 and the following explanations. In the following discussion we consider radio coverage. The connectivity is a function of it and the mapping is based on our link state model (section 5.3).

5. Define the radio coverage requirements. The deployment staff defines the radio coverage requirements based on the application. This includes the service area, the service locations, and the parameters of our approach $ARSS_{Min}$, $ARSS_{RED}$, N_{RED}, T_{perm}, the candidate sites for possible base station installation and bounds on the radio model accuracy.

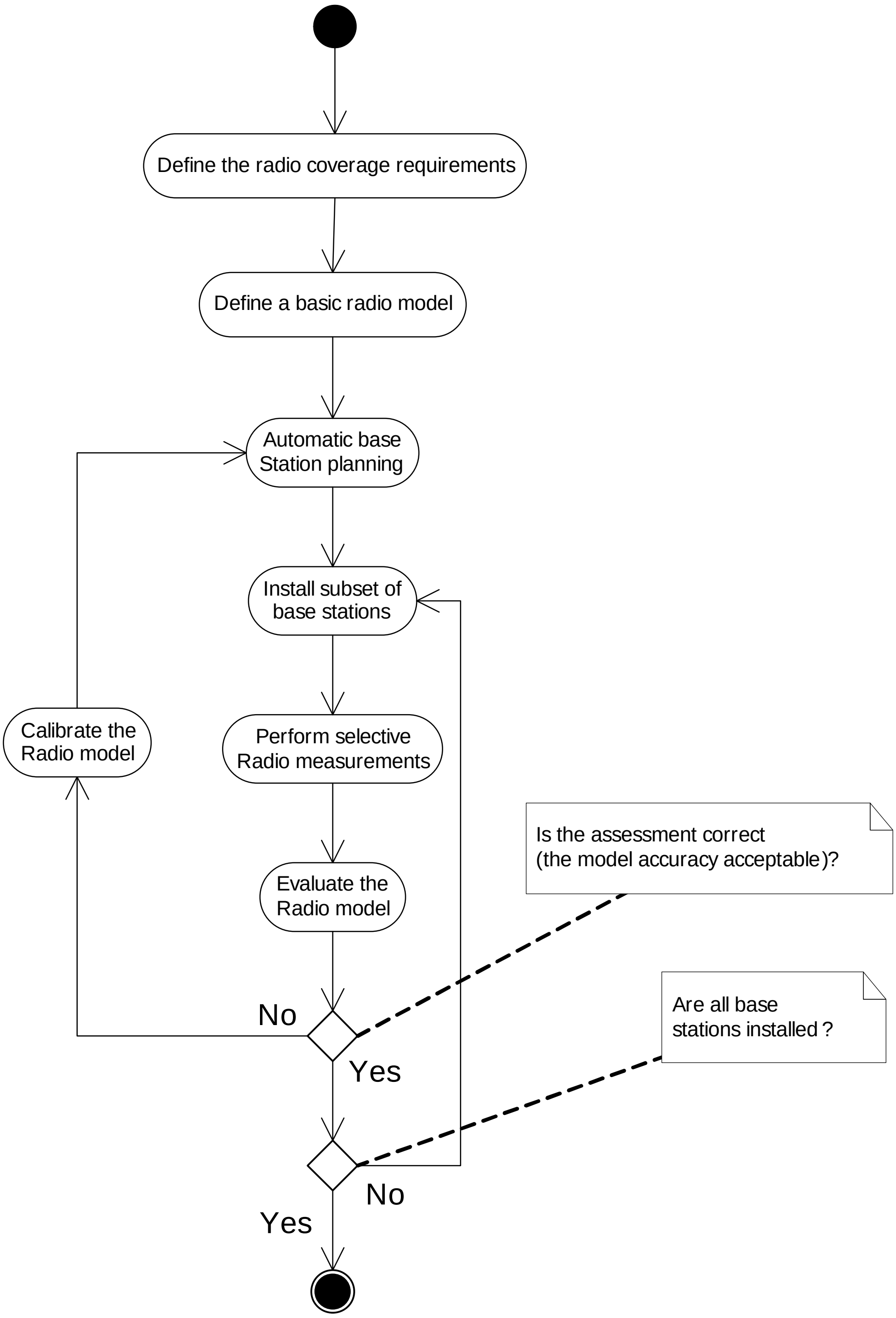
6. Define a basic radio model. The deployment staff gives a first definition of a radio propagation model (section 4.2). This includes information about the different environment types. The parameters for the different environment types are set to some default values from the literature or from previous experience in the operating environment.

7. Automatic base station planning. Based on the defined requirements and radio propagation model the base station planning algorithm (section 5) determines the number and positions of base stations to be installed.

8. Install subset of base stations. The deployment staff installs a subset the proposed base stations. At the first installation these are few (up to 3-4) base stations which allow performing first measurements in the environment. It is a subset and not all base stations, because at the initial step the radio propagation model is not calibrated to the real environment. Therefore some higher discrepancies between the prediction and reality are expected. When the model is calibrated based on real measurements and the prediction accuracy increase, the subset of the installed base stations at this step also increase.

9. Perform selective Radio measurements. The deployment staff performs manual ARRS measurements at selected service locations in the service area.

Algorithm A.1 Radio coverage deployment algorithm



10. Evaluate the Radio model. The radio propagation model is evaluated by comparing the model's behavior to the measured ARSS values, from the previous step.

11. Calibrate the Radio model. If the model accuracy is not within acceptable bounds, model calibration (section 4.3) is performed and the process is repeated starting at step 2.

12. If the model accuracy is within acceptable bounds and the total number of installed base stations has not been reached, the process is repeated starting at step 3.

13. Radio coverage deployment ends successfully when the radio propagation model's accuracy is acceptable and all base stations have been installed.

The specified deployment method is a systematic way for initial installation of a wireless mesh network. The deployment proceeds stepwise in a continuous iteration of planning, installation, verification and adjustment. In this way this approach preserves the invested time and effort in the deployment and avoids trial and error. The result is a radio coverage in redundant state and a radio model which is calibrated and up-to-date to the environment, based on ARSS measurements.