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DYNAMIC RESOURCE MANAGEMENT IN RADIO NETWORKS

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Summary of the Ph.D. Dissertation

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Budapest, Hungary
2009

1 Introduction

The radio spectrum is a scarce, valuable and thus expensive resource, but the available frequency bands are less and less. The substantial fraction of the allocated spectrum is underutilised, the utilisation varies rapidly in time and space.

These spatial and temporal spectrum variations and the currently used rigid spectrum allocation policies result in the fact that a substantial fraction of the spectrum is wasted at a given time and place [12, 16, 4]. This is the motivation for a more spectrum efficient technique, called Dynamic Spectrum Allocation (DSA), where the spectrum usage rights may vary in time and space in a finer scale. Allocating the spectrum dynamically would have significant economic benefits and would greatly improve citizens choice and access to new technologies and services at low prices [2].

The dynamic spectrum allocation initiates a market-based spectrum allocation method. There are two distinct policies that could be introduced: "trading" of frequencies makes it possible to transfer spectrum usage rights in a short timescale, and "liberalisation" ensures the service and technology neutrality. Introduction of both trading and liberalisation could lead to more efficient use of spectrum [3][2]. This process is supported by the European Commission. According to the Communication from the Commission to the Council [3]: "Reforming spectrum management in the EU to introduce a market-based approach to spectrum distribution constitutes a major challenge. But it is worth accepting since an effective introduction of spectrum markets would be:

- beneficial in terms of the gains to Europe in competitiveness, in innovation potential and in strengthening the internal market as well as in increasing the variety of services offered to the consumer, along with the positive effects on the creation of jobs and external trade;

- timely and necessary because spectrum management as practised so far has reached its limits due to technological progress, increasing demand on spectrum resources and the speed of changing business cases and markets;

- feasible in the proposed time frame."

Dynamic spectrum allocation can be realised in a centralised or distributed manner. For military applications the latter one is only acceptable [1], but for commercial applications, because of the existing architecture the aggregation of regional demands and the centralisation of spectrum management decisions is easily realisable and leads to a simpler solution. For a more detailed overview on centralised dynamic spectrum allocation solutions refer to [6] [7] [4] and references therein, as well as to the publications of the Drive, Overdrive and Winner EU projects [10][11][9].

Within the centralised solutions we can distinguish priority access based proposals (where spectrum is dedicated to the primary system –usually the license owner– and the secondary system may only access the same spectrum as long as it does not cause significant interference to the primary system) and equal-right access proposals.

My dissertation focuses on a centralised equal-right access dynamic spectrum allocation framework, that ensures the "trading" of frequencies by allowing the transfer of spectrum usage rights in a short timescale for small regions and ensures the service and technology neutrality according to the Communication from the European Commission to the Council [3]. I also propose an auction and pricing method that –in contrast to the previous proposals [14] [15][8]– determines prices paid by the service providers by taking the interference between the regions into account and this way encourages new, innovative solutions that cause little interference and are able to cooperate with other technologies.

2 Research Goals

The aim of the first theses group is to establish a dynamic spectrum allocation framework that provides the possibility to replace today's rigid spectrum allocation method by a market based solution. Within the theses group I first propose a general framework modelling the interaction of different service providers operating in different regions and define metrics to describe spectrum quality. Then I investigate the gains achievable by dynamic spectrum allocation, propose two allocation models and determine the optimal spectrum allocation within each model.

The second theses group investigates pricing and auction. I propose a one-shot multi-bid auction model that takes specialities of dynamic spectrum allocation into account and fits into the framework proposed in the first theses group. I also investigate the possibilities of quick and efficient evaluation.

3 Methodology

The results of the first part are based on mathematical modelling and analysis. I used linear programming and simulated annealing methods to find the optimal allocations. The framework was validated by a simulation tool developed in MATLAB environment.

The second part proposes a one-shot multi-bid second price auction-based model using methods of game theory and analytical investigation of the possibilities of a quick and efficient evaluation. The validation of the system was carried out by means of a simulation tool I created in MATLAB and Java environments.

4 New Results

The results introduced in this section are grouped according to two main topics. The first thesis group defines a spatio-temporal dynamic spectrum allocation framework, determines the achievable gains using DSA, proposes two allocation models and gives the optimal spectrum allocation in case of both models. The second thesis group investigates auction and pricing. It proposes a one-shot multi-bid auction model and investigates the possibilities of quick and efficient evaluation.

4.1 Spatio-temporal DSA framework

Theses 1. *[J1, J2, C4, C5, C6, C7] Spatio-temporal dynamic spectrum allocation framework.*

The basis of the framework is dividing the area into smaller regions assuming that within each region the spatial distribution of the demands is homogeneous, demands vary only in time.

Questions arising within the framework:

- How to model the interaction between regions and different technologies, i.e., the interference caused by service providers?
- What metrics can be defined in the model for measuring the efficiency of dynamic spectrum allocation?
- What shall be the principle of spectrum distribution? How to handle interaction of different service providers in different regions? How to model the sensitivity of service providers to interference? Interference in neighboring regions may be compensated (Thesis 1.1) or we may introduce a "tolerance" threshold for each provider. (Thesis 1.4)
- What is the optimal allocation (in the before-mentioned two models) that imposes –assuming fix available spectrum amount– minimum disturbance on the providers? Is the allocation feasible at all, with the available spectrum band? (Theses 1.3 and 1.6) What is the minimum necessary spectrum amount to serve all demands? (Theses 1.2 and 1.5)

In the framework I propose dynamic spectrum allocation is interpreted as follows. The available area is divided into smaller regions; such a region can be for example different parts of a city (business quarter, downtown, residential area, etc.). The system handles temporal demands in each region. Time is divided into allocation periods; one allocation periods are in the order of hours, the framework does not aim at dynamic allocation at the call level in cellular networks. In each reallocation period service providers can bid for spectrum blocks with different sizes –according to the user demands. The framework aims at modelling disturbance (interference) between the regions and ensuring only such spectrum allocations in which services provided for users are not ruined by interference. Formally, let the available spectrum block (Coordinated Access Band) be $S_{CAB} = (\check{s}, \hat{s})$. The available area is divided into K regions. Within one regions M service provider compete for the available resources. The spectrum block assigned to the m-th provider in the k-th region at time t:

$$S_{m,k}(t) = (\check{s}_{m,k}(t), \hat{s}_{m,k}(t)) \,. \tag{1}$$

Let us denote the size of the allocated spectrum by $|S_{m,k}(t)|$, i.e.

$$|S_{m,k}(t)| = \hat{s}_{m,k}(t) - \check{s}_{m,k}(t). \tag{2}$$

I propose metrics characterising the quality of the spectrum band B available for the m-th provider in the k-th region, that is

$$\Xi_{m,k}(B, \varepsilon, \eta) = \frac{1}{|B|} \int_B \xi_{m,k}(\lambda, \varepsilon, \eta)\, d\lambda, \tag{3}$$

where

$$\xi_{m,k}(\lambda, \varepsilon, \eta) = \sum_{\forall i,j:(i,j)\neq(m,k)} \varepsilon^{(i)}_{k\leftarrow j} \cdot \eta_{m,i} \cdot I_{\{\lambda\in S_{i,j}\}}, \tag{4}$$

and after the integration

$$\Xi_{m,k}(B, \varepsilon, \eta) = |B|^{-1} \sum_{\forall i,j:(i,j)\neq(m,k)} \varepsilon^{(i)}_{k\leftarrow j} \cdot \eta_{m,i} \cdot |B \cap S_{i,j}|; \tag{5}$$

In the above expressions ε and η are two general parameters I propose to describe the disturbance caused by different providers in case of spatio-temporal DSA. $\varepsilon^{(m)}_{l\leftarrow k}$ is the geographic coupling parameter, which describes the disturbance the m-th provider operating in the k-th region causes in the l-th region; whereas the $\eta_{m,n}$ technology coupling parameter characterises the coupling between the technologies used by the m-th and n-th providers.

In the model interference causes the degradation of the spectrum quality. The extent of interference depends on the geographical location and the parameters of the used technology. Disturbance caused by interference can be split into two independent components. The geographical coupling parameter describes the grade of disturbance caused by a provider operating in the same frequency range in the neighboring (or further) region. The technology coupling parameter describes how much of this disturbance can be "filtered out" depending on the used technology.

Practically, the value of the $\varepsilon_{l \leftarrow k}^{(m)}$ geographical coupling parameter can be expressed as the product of the $s_{k,m}^{max}$ allowed maximal power spectral density at the region borders and the $\varepsilon_{k \leftarrow l}$ signal attenuation between regions R_l and R_k:

$$\varepsilon_{l \leftarrow k}^{(m)} = s_{k,m}^{max} \cdot \varepsilon_{k \leftarrow l}. \tag{6}$$

For example, according to the Okumura-Hata propagation model for urban (medium city) environment [13] $\varepsilon_{k \leftarrow l}$ can be calculated as:

$$\varepsilon_{k \leftarrow l}^{[dB]} = -A^{[dB]} \left(d_{k,l}^{[km]} \right) = -130.52 - 10 \cdot \lg \left(d_{k,l}^{[km]} \right), \tag{7}$$

where attenuation A depends on the distance $d_{k,l}^{[km]}$ between regions R_k and R_l. For neighboring sectors $\varepsilon_{k \leftarrow l}$ is approximately one.

The value of the radio technology coupling parameters $0 \leq \eta \leq 1$ can be determined by detailed simulations for different radio technology pairs. This parameter aims at describing the "extent of coexistence"of different radio technologies its value is influenced by a number of characteristics of the used technology (e.g., signal processing technology, synchronization, advance knowledge, etc.). The smaller of the value of this parameter the better the technology is able to filter other technologies causing interference.

The cumulative disturbance is the product of the geographical and technology coupling parameters. To determine the disturbance imposed on the B spectrum block offered to one provider let us denote the disturbance on the spectrum block by $\Xi_{m,k}(B, \varepsilon, \eta)$ from the point of view of the m-th provider operating in the k-th region. $\xi_{m,k}(\lambda, \varepsilon, \eta)$ in (3) the needed for this calculation is the disturbance imposed on λ frequency from the point of view of the m-th provider in the k-th region; i.e. according to (4) we have to sum up the disturbances on band B, as in (4) $I_{\{\lambda \in S_{i,j}\}}$ indicates whether the λ frequency is assigned to the i-th provider in the j-th region.

Achievable Gains In case of the currently used static spectrum allocation the frequency usage rights are granted for large areas (usually the whole area of a country) and long terms (for years). This means that following today's rigid allocation policy a provider has to allocate (using the notations of the framework I proposed)

$$S_m^f = \max_{\tau, \kappa} |S_{m,\kappa}(\tau)| \tag{8}$$

amount of spectrum slice in order to be able to fulfil demands all the time in all areas. Furthermore, to serve the demands of all providers

$$S^f = \sum_{m=1}^{M} S_m^f \tag{9}$$

amount of spectrum is necessary.

It is worth investigating, what gains we can achieve with the introduction of dynamic spectrum allocation from the provider's and also from the regulator's point of view. The provider's gain results from the fact that it will be able to follow the variation of user demands in time and in space and it will be sufficient to require the spectrum according to the local needs. The regulator's gain results from the "disengaged" spectrum blocks due to dynamic spectrum allocation.

I proposed to use the following metrics for the comparison of DSA and rigid allocation systems:

- Temporary provider gain resulted from temporal DSA:

$$PG_m^t(t) = 1 - \frac{|S_m(t)|}{S_m^f}; \tag{10}$$

- Provider gain resulted from spatial DSA:

$$PG_{m,k}^s = 1 - \frac{S_{m,k}}{S_m^f}; \tag{11}$$

- Temporary provider gain resulted from spatial- and temporal DSA:

$$PG_{m,k}^{st}(t) = 1 - \frac{|S_{m,k}(t)|}{S_m^f}; \tag{12}$$

- Average provider gain:

$$PG_m^{avg} = \int_T PG_m^t(t)dt; \tag{13}$$

- Guaranteed temporary regulator gain:

$$RG(t) = 1 - \frac{\max_{m,k}(\hat{s}_{m,k}(t)) - \min_{m,k}(\check{s}_{m,k}(t))}{S^f}; \tag{14}$$

- Average regulator gain:

$$RG^{avg} = \int_T RG(t)dt. \tag{15}$$

As first step, let us investigate how much gain would a provider (the m-th provider) acquire if only temporal dynamic spectrum allocation was introduced. In this case the provider has to request the highest amount of spectrum ($|S_m(t)|$) demanded over the whole service area from the spectrum broker. So the gain compared to rigid spectrum allocation can be calculated according to (10).

If we introduced only spatial dynamic spectrum allocation (i.e., providers could request spectrum for smaller regions but for long term), then the m-th provider operating in the k-th region has to request the highest demand in the whole time period in the region ($S_{m,k}$) from the spectrum broker. In this case the gain of the provider resulted from spatial dynamic spectrum allocation can be determined according to (11).

In case spatio-temporal dynamic spectrum allocation is introduced, the provider has to request only the highest demand in the given region within the given time period ($|S_{m,k}(t)|$) from the spectrum broker. The achievable gain is the highest in this case and can be given by (12).

Gains can be averaged in time so determining the average provider gain resulted from temporal dynamic spectrum allocation for a given time period (13) and by extending (13) instead of the temporary gain from temporal DSA the integrating the temporary gain from spatio-temporal DSA the provider gain can be also determined for a given region.

Spatial averaging is also possible, but in this case further parameters are needed that describe the relation of the regions (e.g., area proportions, average spectrum price rate within one region, etc.).

From the regulator's point of view gain results from the size of the spectrum that serves all demands in all regions, in other words the size of the "disengaged" spectrum compared to rigid spectrum allocation. The most important characteristic is the spectrum size which serves all demands in one time period, i.e., the distance between the lowest value of the starting points and the highest value of the end points of the allocation, and its relation to rigid spectrum allocation. This is the guaranteed temporary regulator gain whose value can be calculated according to (14). From the time variance of this metrics we can determine (by probabilistic methods or simply considering the minimum value of a longer time period) how much of the previously used spectrum can be disengaged for other purposes by introducing dynamic spectrum allocation. The average gain can also be determined based on (15).

Compensation model After determining the interference imposed on the providers the next task is the allocation of sufficient amount of spectrum, i.e., to model the providers' relation to interference. Theses 1.1 - 1.3 describe a so-called compensation model. The basic idea of this model is that providers do not request spectrum directly, but a transmission channel with specified capacity. It is the task of the spectrum-estimators to determine the sufficient spectrum block size to the requested transmission capacities. This is a complex problem as it depends on the environment (interference imposed on the block). Let us denote by $b_{m,k}$ the bandwidth needed for the requested digital transmission channel with given technology in case there is no interference. In this model the interference arising in the noisy environment is compensated with additional spectrum blocks.

Thesis 1.1 describes the feasibility conditions of a given spectrum allocation in the compensation model. The method proposed in thesis 1.2 determines the smallest spectrum size sufficient to serve all demands (that is the maximal guaranteed regulator gain); furthermore, it determines the starting and end points of the corresponding spectrum allocation. Thesis 1.3 proposes a method to check the feasibility of the allocation for the given demands in case of a fixed amount of available spectrum and determines the minimal interference allocation.

Thesis 1.1. *[C4] In case of the compensation model a* $\mathbf{S} = (\mathbf{S}_1, \ldots, \mathbf{S}_M)$ *allocation (where* $\mathbf{S}_m = (S_{m,1}, \ldots, S_{m,K})$*) is feasible if the spectrum blocks used by the providers (*$\{S_{m,k}\}$*) fulfil the following conditions:*

$$\begin{aligned} S_{m,k} \cap S_{n,k} &= \emptyset, \quad \forall m, n, k, & (16) \\ |S_{m,k}|(1 - \delta\xi(S_{m,k})) &\geq b_{m,k}, \quad \forall m, k, & (17) \end{aligned}$$

where δ *is the compensation constant and* $\Xi_{m,k}(S_{m,k}, \varepsilon, \eta)$ *characterises the allocated spectrum block from the interference's point of view and can be calculated according to equation (*5*).*

Condition (16) ensures that two providers within one region never get the same spectrum slice. Condition (17) means that a provider needs as much more allocated spectrum block as compensates the decrease in capacity due to interference. Parameter δ in this condition is a so-called "compensation constant" that gives the amount of spectrum block needed to compensate a unit measure of disturbance.

Thesis 1.2. *[C4] I determined a set of conditions that –if satisfied by an allocation– determines the smallest spectrum size sufficient to fulfil all demands. Let*

$$c_{(\{m,k\},\{n,l\})} = \begin{cases} 1, & \text{if } k = l \\ \delta\eta_{m,n}\varepsilon_{k,l}, & \text{otherwise} \end{cases} \tag{18}$$

furthermore,

$$z_{(i,j)} = |S_i \cap S_j| = \max\{0, \min\{\hat{s}_i, \hat{s}_j\} - \max\{\check{s}_i, \check{s}_j\}\}, \tag{19}$$

and

$$\check{y}_{(i,j)} = I_{\{\check{s}_i \leq \check{s}_j\}}, \hat{y}_{(i,j)} = I_{\{\hat{s}_i \leq \hat{s}_j\}}. \tag{20}$$

Then the solution of the Integer Linear Program defined as:

$$\check{s} \leq \check{s}_i \leq \hat{s}_i \leq \hat{s} \quad \forall i \in V, \tag{21}$$

$$\hat{s}_i - \check{s}_i - \sum_{\forall (i,j)\in E} z_{(i,j)} \cdot c_{(i,j)} \geq b_i s_0 \quad \forall i \in V, \tag{22}$$

$$\begin{aligned}
z_{(i,j)} &\geq \hat{s}_j - \check{s}_j - S \cdot (\hat{y}_{(i,j)} + (1 - \check{y}_{(i,j)})), \\
z_{(i,j)} &\geq \hat{s}_i - \check{s}_j - S \cdot [(1 - \hat{y}_{(i,j)}) + (1 - \check{y}_{(i,j)})], \\
z_{(i,j)} &\geq \hat{s}_j - \check{s}_i - S \cdot [\hat{y}_{(i,j)} + \check{y}_{(i,j)}], \\
z_{(i,j)} &\geq \hat{s}_i - \check{s}_i - S \cdot [(1 - \hat{y}_{(i,j)}) + \check{y}_{(i,j)}],
\end{aligned} \tag{23}$$

$$\hat{s}_i \leq s' \quad \forall i \in V, \tag{24}$$

determines the smallest spectrum size sufficient to serve the given demands (i.e., maximum regulator gain); and also determines the starting and end points of the spectrum blocks in this allocation.

I modelled the problem with an undirected graph, where one vertex represents one provider operating in a region, the decrease in spectrum quality (i.e., interference between the two vertices) is represented by the cost of the edges connecting the vertices (see (18)).

The task is to find for each vertex the corresponding $S_i = (\check{s}_i, \hat{s}_i)$ optimal spectrum block. Let us define for each edge a variable $z(i,j)$ that represents overlapping (see (19)).

Introducing the working variables $\check{y}_{(i,j)} = I_{\{\check{s}_i \leq \check{s}_j\}}$ and $\hat{y}_{(i,j)} = I_{\{\hat{s}_i \leq \hat{s}_j\}}$ the problem can be formulated the above described way, the aim is to minimise s'. The solution of this problem determines the size of the smallest amount of spectrum (s') required to fill the given set of demands (b_i); the $S_i = (\check{s}_i, \hat{s}_i)$ variables contain the starting and end points of the spectrum blocks allocated to each provider.

Thesis 1.3. *[C4] I determined a set of conditions that –if satisfied by an allocation– determines the allocation with the smallest cumulative interference. Using the notations of Thesis 1.2 and introducing f' for the cumulative interference, the solution of the Integer Linear Program defined by equations (22) and (23) of the previous thesis and*

$$0 \leq \check{s}_i \leq \hat{s}_i \leq S_{CAB}, \quad \forall i \in V, \tag{25}$$

$$\sum_{\forall (i,j)\in E} z_{(i,j)} \cdot c_{(i,j)} \leq f', \quad \forall (i,j) \tag{26}$$

determines the feasibility of the allocation over the available spectrum and the allocation with the minimal interference.

The modelling of this problem is the same as the model described in Thesis 1.2. Equations for compensation and overlapping are the same as (22) and (23) in Thesis 1.2.

Equation (25) defines the limits of the bandwidth available for DSA, (26) calculates the cumulative interference; this way minimizing f' leads to the allocation with the smallest cumulative interference.

If the problem is solvable it is possible to fulfil all demands within the available spectrum band (S_{CAB}); variables $S_i = (\check{s}_i, \hat{s}_i)$ contain the allocation with minimal interference.

Interference tolerant model As a second approach to the spectrum allocation problem I defined the "interference tolerant" model. Theses 1.4-1.6 describe findings regarding this model. The basis of the allocation is that different technologies can tolerate disturbance to different extent. Therefore I proposed to introduce two parameters (α and β) to describe the interference tolerance level of the provider. Parameter β_m describes the maximal average interference that the provider is able to tolerate, the α_m parameter represents the maximal interference that must not be exceeded by the allocation in any frequency. Thesis 1.4 determines the feasibility conditions of an allocation within the interference tolerant model. Methodology proposed in Thesis 1.5 determines the smallest spectrum amount sufficient to fulfil all demands (i.e., the guaranteed regulator gain is maximal); furthermore, it gives the starting and end points of the spectrum blocks belonging to this allocation. Procedure of Thesis 1.6 check the feasibility of an allocation with a limited amount of available spectrum, and also gives the smallest interference allocation.

Thesis 1.4. *[J1, C2, C5] Assuming that the providers are restricted not to exceed the s^{max} maximal allowed spectral power density at the region borders, in case of the interference tolerant model an $\mathbf{S} = (\mathbf{S}_1, \ldots, \mathbf{S}_M)$ allocation (where $\mathbf{S}_m = (S_{m,1}, \ldots, S_{m,K})$) is feasible if the spectrum blocks used by the providers ($\{S_{m,k}\}$) satisfy the following conditions:*

$$\Xi_{m,k}(S_{m,k}, \varepsilon, \eta) \leq \beta_m, \quad \forall m, k, \tag{27}$$

$$\max_{\lambda \in S_{m,k}} \xi_{m,k}(\lambda, \varepsilon, \eta) \leq \alpha_m, \quad \forall m, k. \tag{28}$$

Where substituting $\varepsilon^{(i)}_{k \leftarrow j} = s^{max}_{i,j} \cdot \varepsilon_{k \leftarrow j}$ into (4) and (5) we get

$$\Xi_{m,k}(S_{m,k}, \varepsilon, \eta) = |B|^{-1} \sum_{\forall i,j:(i,j) \neq (m,k)} \varepsilon_{k \leftarrow j} \cdot \eta_{m,i} \cdot s^{max}_{i,j} \cdot |B \cap S_{i,j}|; \tag{29}$$

and

$$\xi_{m,k}(\lambda,\varepsilon,\eta) = \sum_{\forall i,j:(i,j)\neq(m,k)} \varepsilon_{k\leftarrow j}\cdot\eta_{m,i}\cdot s_{i,j}^{max}\cdot I_{\{\lambda\in S_{i,j}\}}. \tag{30}$$

In the proposed model the providers are restricted not to exceed a maximal spectral power density ($s_{i,j}^{max}$) at the region borders. This limit can be checked and its value adjusted for each region and provider. Introducing this parameter the $\varepsilon_{k\leftarrow j}^{(i)}$ parameter of the framework can be split into the product of the limit of the spectral power density of the provider ($s_{i,j}^{max}$) and the signal attenuation between the two regions ($\varepsilon_{k\leftarrow j}$):

$$\varepsilon_{k\leftarrow j}^{(i)} = s_{i,j}^{max}\cdot\varepsilon_{k\leftarrow j}. \tag{31}$$

Substituting (31) into (4), (30) is resulted that measures the interference at the given frequency. Substituting (30) back into (3) after the integration the result is (29) of the thesis, which is the metrics of spectrum quality -in this case the average interference within the allocation.

Thus (27) guarantees that the average interference remains below β_m, and (28) limits the maximal interference in any frequency to the value of α_m.

Thesis 1.5. *[J1, C5] The minimum of the function below determines the allocation for the interference tolerant model which allows to serve the given allocation vector* ($\mathbf{a}$) *using the minimum amount of spectrum (maximal guaranteed regulator gain): Let*

$$\mathbf{s} = (\check{s}_{1,1},\ldots,\check{s}_{1,K},\ldots,\check{s}_{M,1},\ldots,\check{s}_{M,K}), \tag{32}$$

and

$$|S| = \max(\hat{s}_{m,k}) - \min(\check{s}_{m,k}). \tag{33}$$

Furthermore, let us define the allocation vector $\mathbf{a}$ *the following way:*

$$\mathbf{a}((m-1)K+k) = \hat{s}_{m,k} - \check{s}_{m,k}. \tag{34}$$

In this case

$$E(\mathbf{s},\mathbf{a}) = -\frac{S_{CAB}-|S|}{S_{CAB}} + P_f, \tag{35}$$

where

$$P_f = \sum_{m=1}^{M}\sum_{k=1}^{K}\left(I_{\{\Xi(S_{m,k})<\beta_m\}} + I_{\{\min\limits_{\lambda\in S_{m,k}}\xi_{S_{m,k}}(\lambda)<\alpha_m\}}\right). \tag{36}$$

The minimum of the defined target function determines the allocation for the interference tolerant model which allows to serve the given allocation vector ($\mathbf{a}$) *using the minimum amount of spectrum (maximal guaranteed regulator gain). Equation (33) determines the size of this spectrum band.*

In case of complex optimization tasks a frequently used method is the definition of a state vector (state space) describing the system and a so-called target function – within this domain– that reaches its minimum value at the optimum point. I defined the state vector for the above described problem according to (32). Thus, the S spectrum allocation can be represented by the $\mathbf{s}$ state vector and the $\mathbf{a}$ allocation vector.

The first part of the target function defined in (35) measures the non-utilized fraction of the available spectrum (S_{CAB}), whilst the value of the P_f penalty function is zero only if the (27) and (28) feasibility conditions hold true for all spectrum blocks, otherwise the value of the penalty function is at least one.

Corollary 1. *Consequently, the E target function of (35) has the following characteristics:*

- *if the value of the function is positive, then the feasibility conditions are not satisfied;*
- *if the minimum of the function is positive, then the given demand set is not feasible to serve within the given S_{CAB} available spectrum band;*
- *if the value of the energy function is negative, the arrangement is one possible solution for the allocation;*
- *smaller values of the energy function mean allocations closer to the optimal allocation.*

Optimisation can be done by means of simulated annealing where the energy of the system is defined by (35) and (36). In every step the simulated annealing algorithm investigates some neighbors ($\mathbf{s}'$) of the actual state ($\mathbf{s}$) and probabilistically decides if the system stays in the $\mathbf{s}$ state with $e = E(\mathbf{s})$ energy or move to the $\mathbf{s}'$ state with $e' = E(\mathbf{s}')$ energy.

In the algorithm I propose the new neighbors are generated from the old state vector by adding a Gaussian-distributed random value to each element of the current state vector, that is:

$$\mathbf{s}' = \mathbf{s} + X\mathbf{e}_Y, \quad X \sim \mathcal{N}(0, \sigma), \quad Y \sim \mathcal{U}_{MK}, \tag{37}$$

where $\mathbf{e}_i$ is the unit vector whose i-th element is one, Y is a uniformly distributed discrete random variable in $[1, MK]$. The mean of the state-shift variable X is zero, and the standard deviation is set to be $S_{CAB}/4$.

The probability of making the transition from the current state s to a candidate new state s' is a function $P(e, e', T)$ of not just the state energies e and e', but a global time-varying parameter (T). I used the following function to determine the probability of a transition:

$$P(e, e', T) = e^{\frac{e-e'}{T}}. \tag{38}$$

The function used for the decrement of parameter T is $T_{k+1} = \alpha \cdot T_k$, where $T_0 = 1$ and $\alpha = 0.98$

Thesis 1.6. *[J1, C5] The minimum of the target function defined below determines –in case of interference-tolerant model– the allocation with the minimal interference: Using the assumptions and definitions from Thesis 1.5,*

$$E(\mathbf{s}, \mathbf{a}) = -\frac{\Xi_{max} - \Xi(S_{CAB})}{\Xi_{max}} + P_f, \tag{39}$$

where

$$\Xi(S_{CAB}) = \sum_{\forall m,k} \Xi_{m,k}(S_{m,k}), \tag{40}$$

furthermore,

$$\Xi_{max} = \sum_{\forall m,k} |S_{m,k}|^{-1} \cdot \sum_{\forall i,j:(i,j)\neq(m,k)} \varepsilon_{k\leftarrow j} \cdot \eta_{m,i} \cdot s_{i,j}^{max} \cdot |S_{CAB}|. \tag{41}$$

The minimum of the defined target function determines the allocation for the interference tolerant model with the minimal arising interference. Furthermore, the negative value of the function indicates that the allocation is feasible.

The state vector describing the system is the same as defined in Thesis 1.5. The target function defined in (39) also consists of two parts. The first term measures how much less the interference is than the theoretical maximum, Ξ_{max} is the theoretical maximum value of interference in the system, when all providers submit maximum demands. The second term of the target function is the same penalty function as defined in Thesis 1.5.

Corollary 2. *Consequently, the E target function defined by (39) has the same characteristics as described in Corollary 1.*

4.2 Real time auction and pricing

Theses 2. *[B1, J1, C1, C3] Real time auction and pricing in the spatio-temporal DSA management framework.*

Besides the definition of the framework, the modelling of interaction between the regions and determining the optimal allocation, the other main topic is the "market for frequencies" for dynamic spectrum allocation; establishing an adequate, real time auction- and pricing DSA management framework.

In Thesis 2.1 I propose an allocation model that takes the specialities of DSA systems into account, i.e., it is able to adapt to the variations of spectrum demands in time and space. The aim of the proposed model is to follow variations during the day; the re-allocation period is typically 1-2 hours. The model is centralised, i.e., the demands and bids of the providers are submitted to a central spectrum broker that determines the optimal allocation, the prices to be paid by the providers and grants exclusive licenses to the bought spectrum blocks for the next re-allocation period.

In order to find the optimal allocation a number of feasibility checks have to be carried out within one bidding period. The quick feasibility check is essential for real-time operation. For this problem Theses 2.2 and 2.3 propose solutions. The second task is finding the most efficient allocation; I propose a quick, rule-based algorithm for this in Thesis 2.4.

Auction Model The available spectrum is re-allocated at given time periods. (Not at call level, but one a time scale appropriate to follow daily variations. This means typically 1-2 hour time intervals.) Before the start of each period the providers submit their bids to a centralised spectrum broker entity. The spectrum broker determines the prices to be paid by the providers and the optimal allocation that maximises "social welfare".

Since the convergence time of the interactive auctions may be long and may cause significant signalling traffic; furthermore, the demand function of the providers is typically non-continuous and contains only a few bids, I proposed a one-shot multi-bid auction model for pricing.

Let $\mathcal{I} = \{1, \ldots, i, \ldots, I\}$ denote the set of players. Since the demands of one provider may be different in different regions, I handle the providers separately in each region, i.e., $I = M \cdot K$.

The i-th player submits $N^{(i)}$ two-dimensional bids to the spectrum broker:

$$B_i = \{b_{i,1}, \ldots, b_{i,N^{(i)}}\}, \tag{42}$$

where

$$b_{i,n} = (q_{i,n}, p_i(q_{i,n})), \quad n = 1, \ldots, N^{(i)}, \tag{43}$$

and q denotes the size of the requested resource and $p(q)$ represents the price offered for this resource.

From the collected bids the spectrum broker creates the input parameter of the pricing algorithm, the multi-bid profile:

$$B = (B_1, \ldots, B_I). \tag{44}$$

On this basis and using A allocation rule and the corresponding C pricing scheme the spectrum broker determines for all $i \in \mathcal{I}$ players the optimal a_i allocation and the corresponding c_i price.

The A allocation rule returns an allocation vector,

$$A(B) = \mathbf{a} = (a_1, \ldots, a_I), \tag{45}$$

where

$$a_i \in \{0, b_{i,1}, \ldots, b_{i,N^{(i)}}\}, \quad i = 1, \ldots, I, \tag{46}$$

that is, the size of one of the resources requested by the i-th player or zero, when neither of the bids are feasible.

The C pricing scheme for one allocation is

$$C(A(B)) = C(\mathbf{a}) = (c_1, \ldots, c_I), \quad i = 1, \ldots, I, \tag{47}$$

where $c_i \leq p_i(a_i)$ is the price the i-th player has to pay for using the a_i sized spectrum slice. This value cannot be higher that the maximum price offered by the provider.

Thesis 2.1. *[B1, J1, C1, C3] For spectrum auctions in dynamic spectrum allocation systems I proposed a one-shot multi-bid auction model with the following allocation rule and pricing scheme:*

$$A(B) = \tilde{\mathbf{a}} = (\tilde{a}_1, \ldots, \tilde{a}_I) = \arg\max_{\mathbf{a} \in Q^f} \Theta(\mathbf{a}), \tag{48}$$

and,

$$\begin{aligned} c_i(A(B)) &= \theta_i(\tilde{a}_i) - \left[\Theta(\tilde{\mathbf{a}}) - \Theta\left(\tilde{\mathbf{a}}^{(-i)}\right)\right] = \\ &= \sum_{\substack{j=1 \\ j \neq i}}^{I} \left[\theta_j\left(\tilde{a}_j^{(-i)}\right) - \theta_j(\tilde{a}_j)\right], \end{aligned} \tag{49}$$

where

$$\Theta(\mathbf{a}) = \sum_{i=1}^{I} \theta_i(a_i) \tag{50}$$

is the efficiency of the allocation, $\theta_i(a_i)$ is the value the allocation is worth for the i-th player. The proposed solution maximises "social welfare".

The A allocation rule can be defined for a B set of bids the following way:

$$A(B) = \arg\max_{\mathbf{a}\in Q^f} \sum_{i=1}^{I} p_i(a_i), \tag{51}$$

where Q^f is the set of feasible allocations, i.e., for all $\mathbf{a} \in Q^f$ there exists a spectrum allocation $S(\mathbf{a}) = \{S_{1,1}, \ldots, S_{M,K}\}$ where $|S_{m,k}| = a_{(m-1)K+k}$, that satisfies the feasibility conditions (27), (28).

An $\tilde{\mathbf{a}}$ alocation is called *optimal*, if it is the most efficient feasible allocation, i.e.:

$$\tilde{\mathbf{a}} = (\tilde{a}_1, \ldots, \tilde{a}_I) = \arg\max_{\mathbf{a}\in Q^f} \Theta(\mathbf{a}). \tag{52}$$

Comparing (51) and (52) it can be proven that the proposed allocation rule only results the optimal allocation if the players bid according to $p_i(q) = \theta_i(q)$. This can be achieved using a pricing scheme that "forces" the players to let the spectrum broker know how much the spectrum really worth for them. The second price auction is a suitable choice for this purpose. In this case it can be shown that "telling the truth" is the dominant strategy.

Based on these in the followings I assume that the bids of the providers are $(q_i, \theta_i(q_i))$ pairs, prices are determined the following way: Let $B^{(-i)}$ denote the set resulted by deleting the bid of the i-th player from the bid set, i.e.:

$$B^{(-i)} = (B_1, \ldots, B_{i-1}, 0, B_{i+1}, \ldots, B_I). \tag{53}$$

Based on (52) the optimal allocation can be determined for the $B^{(-i)}$ set:

$$\begin{aligned} \tilde{\mathbf{a}}^{(-i)} &= \left(\tilde{a}_1^{(-i)}, \ldots, \tilde{a}_{i-1}^{(-i)}, 0, \tilde{a}_{i+1}^{(-i)}, \ldots, \tilde{a}_I^{(-i)}\right) = \\ &= \arg \max_{\mathbf{a}^{(-i)}\in Q^f} \Theta\left(\mathbf{a}^{(-i)}\right), \end{aligned} \tag{54}$$

where

$$\mathbf{a}^{(-i)} = A\left(B^{(-i)}\right). \tag{55}$$

Based on the rules of second price auction the price to be paid by the i-th provider is:

$$\begin{aligned} c_i(A(B)) &= \theta_i(\tilde{a}_i) - \left[\Theta(\tilde{\mathbf{a}}) - \Theta\left(\tilde{\mathbf{a}}^{(-i)}\right)\right] = \\ &= \sum_{\substack{j=1 \\ j\neq i}}^{I} \left[\theta_j\left(\tilde{a}_j^{(-i)}\right) - \theta_j(\tilde{a}_j)\right]. \end{aligned} \tag{56}$$

The efficiency definition of (50) and the "telling the truth" dominant strategy following from the second price auction results that using the above allocation rule and pricing scheme the achieved optimal allocation is the one that maximises social welfare.

Fast Feasibility Check In order to find an optimal allocation we have to evaluate the feasibility of several allocation vectors. However, the feasibility check is a complex task; on the first hand it is an exhaustive search in an $M \cdot K$ dimensional hyper-cube with an edge length of S_{CAB} (the size of the Coordinated Access Band).

In the proposed model the model parameters can be grouped into two categories: fast varying parameters (spectrum requests) may change at each allocation time, whereas slow varying parameters (technology specific parameters and geographic coupling parameters) change occasionally. Assuming that $\beta = \alpha$ and by fixing the slow varying parameters $(\alpha, \epsilon, \eta, S_{CAB})$ a near real-time feasibility estimation method can be constructed utilizing the characteristics that a hyper-space can be defined in which the feasible and non-feasible allocations are separated by a hyper-surface.

Thesis 2.2. *[C1] I showed that fixing the slow varying parameters a hyper-space can be defined in which the feasible and non-feasible allocations form two disjoint sets that are separated by a hyper-surface. I also proposed a fast algorithm for feasibility check. The method consists of a one-time offline pre-calculation and a fast linear feasibility check.*

Theorem 4.1. *[C1] By fixing the slow varying parameters the feasibility check becomes a set separation problem in the request-space; i.e., there is a hyper-surface that separates the feasible and non-feasible allocations.*

Proof

- All of the feasible allocations are enclosed in a hyper-cube with an edge length of S_{CAB}. If a request exceeds the size of the coordinated access band (S_{CAB}) then the allocation will not be feasible.

- If a spectrum allocation $S = \{S_{1,1}, \ldots, S_{M,K}\}$ is feasible (i.e., the spectrum blocks satisfy (28)) then $S^f = \{S^f_{1,1}, \ldots, S^f_{M,K}\}$ is also feasible $\forall (S^f_{1,1} \leq S_{1,1}, \ldots, S^f_{M,K} \leq S_{M,K})$. E.g., the starting points of the allocation are the same as the original allocation.

- If a spectrum allocation $S = \{S_{1,1}, \ldots, S_{M,K}\}$ is not feasible (i.e., the spectrum blocks do not satisfy (28)) then $S^{nf} = \{S^{nf}_{1,1}, \ldots, S^{nf}_{M,K}\}$ is not feasible either $\forall (S^{nf}_{1,1} \leq S_{1,1}, \ldots, S^{nf}_{M,K} \leq S_{M,K})$.

- It follows from the above statements that in the request-space the feasible and on-feasible allocations are separated into two disjoint sets by a hyper-surface.

□

The feasibility check is a complicated function:

$$Y(\mathbf{a}, \alpha, \epsilon, \eta, S_{CAB}) = \begin{cases} 1, & \text{if } \mathbf{a} \text{ is feasible,} \\ -1, & \text{if } \mathbf{a} \text{ is not feasible.} \end{cases} \tag{57}$$

By fixing the slow varying parameters $(\alpha, \epsilon, \eta, S_{CAB})$ we can construct a fast feasibility check method, i.e.:

$$\hat{Y}(\mathbf{a}) = \hat{y}. \tag{58}$$

Separation by Means of a Convex Polytope The basic idea of the estimation is that we construct an interpolation of the separation surface as a union of hyper-planes, and this leads to a fast feasibility estimation. I note, that the above described characteristics does not ensure that the feasible allocations form a convex polytope. When using this approximation it must always be considered that the error of the approximation may be high. The fast feasibility estimation consists of two phases:

- In the pre-calculation phase the coefficients of the optimal interpolating hyper-surface (as a union of L hyper-planes) are determined. These coefficients need to be re-calculated only if the slow varying parameters have been changed. One hyper-plane is defined as a Cartesian form of the equation of a plane:

$$\sum_{i=1}^{M \cdot K} a_i \cdot w_i = w_0, \tag{59}$$

  where a_i-s are the spectrum requests and w-s are the coefficients of the hyper-plane.

- After the determination of the coefficients (for L hyper planes) the feasibility check is simply a substitution into

$$\hat{Y}(\mathbf{a}) = \operatorname{sgn}\left\{\sum_{l=1}^{L} \operatorname{sgn}\left(\sum_{i=1}^{MK} a_i w_i^{(l)} - w_0^{(l)}\right) - L + 0.5\right\}, \tag{60}$$

  where $w_i^{(l)}$-s are the coefficients of the separation surface.

There are several proposals for the estimation of the hyper-surface in set separation problems. For example in a backpropagation based solution we can start from a learning set $\tau^{(q)} = \{(\mathbf{a}_q, y_q); q = 1 \dots Q\}$, where $\mathbf{a}_q$ is an allocation vector, and $y_q = 1$ if $\mathbf{a}_q$ is feasible, and $y_q = -1$ if $\mathbf{a}_q$ is not feasible.

Let us define $MSE(\mathbf{W})$ as the mean squared error of the estimator, i.e.,

$$MSE(\mathbf{W}) = \frac{1}{Q} \sum_{q=1}^{Q} (y_q - \hat{y}_q)^2. \tag{61}$$

We search for the optimal $\mathbf{W}_{opt}$ matrix, that minimises the mean squared error.

$$\mathbf{W}_{opt} = \min_{\mathbf{W}} MSE(\mathbf{W}). \tag{62}$$

Since backpropagation requires that the activation function (φ) is differentiable we use

$$\mathbf{W}_{opt} = \min_{\mathbf{W}} \frac{1}{Q} \sum_{q=1}^{Q} \left(y_q - Net(\mathbf{a}_q, \mathbf{W})\right)^2, \tag{63}$$

where

$$Net(\mathbf{a}, \mathbf{W}) = \varphi \left\{ \sum_{l=1}^{L} \varphi \left(\sum_{i=1}^{MK} a_i w_i^{(l)} - w_0^{(l)} \right) - L + 0.5 \right\} \tag{64}$$

is the estimator, that results by substituting the sgn function of (60) with a differentiable sigmoidal function φ.

With this substitution W_{opt} can be determined by the following iteration:

$$\mathbf{W}(k+1) = \mathbf{W}(k) - \delta \mathbf{grad}(MSE(\mathbf{W}(k))), \tag{65}$$

where δ is a backpropagation constant and the mean squared error can be calculated by substituting the estimator in (64) into (61), i.e.,

$$MSE(\mathbf{W}) = \frac{1}{Q} \sum_{q=1}^{Q} (y_q - Net(\mathbf{a}_q, \mathbf{W}))^2. \tag{66}$$

Separation by Means of a Multi-Layer Feed-Forward Neural Network It has been proven that standard multi-layer feed-forward networks with as few as one hidden layer using arbitrary squashing functions are capable of approximating any function from one finite dimensional space to another to any desired degree of accuracy, provided sufficiently many hidden units are available. In this sense, multi-layer feed-forward networks are a class of universal approximators.

That is, modifying the Net function in equation 63 as follows we can define a universal approximator for the set separation problem:

$$Net(\mathbf{a},\mathbf{W}) = \varphi\left\{\sum_{l=1}^{L} w_{2,l}\varphi\left(\sum_{i=1}^{MK} a_i w_{1,i}^{(l)} - w_{1,0}^{(l)}\right) - w_{2,0}\right\} \quad (67)$$

Improve the Scalability of the Pre-calculation Phase During the learning set construction in the pre-calculation (non-real time) phase we have to evaluate the feasibility of several allocation vectors. It can be evaluated by an exhaustive search or a heuristic method as proposed in [C9]. In case of a feasible allocation the evaluation is relatively quick as usually more than one feasible allocation exists with the given conditions. However, when the allocation is not feasible an exhaustive search over the hyper-space is required. Although it is an offline task, the scalability of this calculation can be improved by the exclusion matrix introduced below.

Thesis 2.3. *[C1] I proposed an exclusion matrix for the interference tolerant model to fast evaluate the feasibility of an allocation. The rows of the proposed matrix represent cliques of a undirected graph in which the vertices represent one provider of a region, furthermore:*

$$\begin{aligned} &e_{\{m,k\}\{n,l\}} \in E \Leftrightarrow \\ &\left(\left(i_{\{m,k\}\leftarrow\{n,l\}} > \alpha_m\right) \vee \left(i_{\{n,l\}\leftarrow\{m,k\}} > \alpha_n\right)\right), \end{aligned} \quad (68)$$

where

$$i_{\{m,k\}\leftarrow\{n,l\}} = \varepsilon_{k\leftarrow l} \cdot \eta_{m,n} \cdot s_{n,l}^{max}. \quad (69)$$

Let us consider an undirected graph whose vertices represent the service providers of each region. There is an edge between the m-th provider of the k-th region and the n-th provider of the l-th region if the two providers cannot get the same spectrum slice due to the feasibility conditions, (68) and (69).

Let us define an exclusion vector ($\mathbf{x}$) so that the number of the elements of the vector is NK, each element corresponds to a service provider-region pair (player) and in the vector those players get value 1 who cannot get the same spectrum slice.

This vector represents a clique in the above defined graph. Bron and Kerbosch [5] gave an algorithm to compute all cliques in linear time (relative to the number of cliques). I note that it is not necessary to determine all cliques in the graph but the more cliques are determined the more the speed of the non-real time preprocessing can be improved. I also note that cliques are typically small and usually restricted to a region and its neighbors.

To each identified clique let us assign the corresponding exclusion vector then construct an exclusion matrix so that the rows of the matrix are the exclusion vectors:

$$\mathbf{X} = (\mathbf{x_1}; \ldots \mathbf{x_s}). \tag{70}$$

When

$$\max(\mathbf{Xa}) > S_{CAB}, \tag{71}$$

the **a** allocation is not feasible.

Search for an Optimal Allocation According to (52) we have to find a feasible allocation vector that maximises the sum of the efficiency of the allocation. Theoretically, this can be determined by sorting the possible allocation vectors by the efficiency of the allocation, then selecting the first feasible allocation from the sorted list. The structure of the possible allocation vector set ensures that we can find the allocations closer to the optimal iteratively, without having to sort the list.

Thesis 2.4. *[C1] Assuming that bids are ordered so that $q_{i,n} \leq q_{i,n+1}$ for all $1 \leq n \leq N^{(i)} - 1$, and $p(q)$ is monotonously increasing I showed that $\mathbf{r}$ defined based on $r(i) = i_n$ –where i_n is the nuber of the n-th bid of player i– has the following characteristics:*

- *If an $\mathbf{r_f}$ allocation is feasible then all $\tilde{\mathbf{r}}_\mathbf{f}$ allocations are also feasible, for which the $\tilde{r_f}(i) \leq r_f(i)$ equation holds for all $1 \leq i \leq I$. Furthermore, because of the monotonicity of $p(q)$ and the second price auction $\mathbf{r_f}$ is more efficient than $\tilde{\mathbf{r}}_\mathbf{f}$s.*
- *Similarly, if $\mathbf{r_{nf}}$ is not feasible then all $\tilde{\mathbf{r}}_\mathbf{nf}$ allocations are not feasible for which $\tilde{r_{nf}}(i) \geq r_{nf}(i)$ for all $1 \leq i \leq I$.*

The above statements mean that by the evaluation of an allocation a rule is also resulted that determines whether several additional allocations are feasible or not. If we choose the allocation vectors from the space not covered by the above rules the $\mathbf{r_f}$ vectors will converge to the most efficient feasible allocation (optimal allocation).

The bid vector submitted by player i based on (42) and (43) is

$$B_i = \{b_{i,1}, \ldots, b_{i,N^{(i)}}\}, \tag{72}$$

where

$$b_{i,n} = (q_{i,n}, p_i(q_{i,n})), \quad n = 1, \ldots, N^{(i)}. \tag{73}$$

Since the bids are ordered according to

$$q_{i,n} \leq q_{i,n+1} \forall n \in \{1, \ldots, N^{(i)} - 1\}, \tag{74}$$

if an allocation representing $\mathbf{r_f}$ demand is feasible then all $\tilde{\mathbf{r_f}}$ allocations –defined by the above rule– are also feasible, e.g., because the starting points of the two allocations are the same (refer to the proof of Theorem 4.1). Furthermore, the monotonicity of the offered price results that the efficiency of $\mathbf{r_f}$ is greater than or equal to that of all $\tilde{\mathbf{r_f}}$s.

The statement for vectors $\mathbf{r_{nf}}$ and $\tilde{\mathbf{r_{nf}}}$ can be proven similarly.

5 Applicability of the Results

The general framework and proposed metrics in the first thesis group can form the basis of comparison of future systems using dynamic spectrum allocation and the valuation of achievable gains. The interference tolerant and interference compensation models present two different approaches; with the current technological advances the interference tolerant model will soon allow the realisation of dynamic spectrum allocation systems. The interference compensation model can be realised in the future when the technological issues of its application are solved.

The second thesis group proposes an auction and pricing solution that is capable to transact periodic spectrum auctions in future dynamic spectrum allocation systems. The proposed method takes specialities of dynamic spectrum allocation into account, the real price to be payed depends on interference caused by the providers and their noise tolerance level, too. These characteristics encourage the appearance of new, innovative technologies in the market that are able to tolerate disturbances and impose a minimal interference to other technologies present around them.

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