



Simulative Workload Analysis of Police Forces

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Abstract:

This chapter discusses a simulation model for conducting workload analyses of police forces. Due to the high operational heterogeneity and variability, determining reliable profiles for resource utilization and establishing their relationship to response times is a challenging task in and of itself that requires an adequate consideration of several sources of stochastic influence. Prior approaches from police practice mainly consider static ratios (e.g. resources per number of inhabitants or calls for service) in order to estimate capacity demand. Based on an extensive dataset comprising more than two million data points, we derive stochastic process models for all relevant police operations in a major metropolitan area and use a discrete-event simulation to analyse the effects on workloads and capacity utilization of a given fleet of police cars. The simulation model predicts the spatial and temporal occurrence of police operations and dispatches available vehicles from different districts, in order to model resource sharing in emergency response. This provides key insights into the required capacity over time and constitutes a crucial first step for an adequate capacity planning.

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1 Introduction

A crucial task in the planning of police forces is guaranteeing an adequate allocation of resources (personnel, vehicles, etc.) to police districts such that an effective and robust service can be provided and emergency response times are kept as low as possible. The vast majority of planning approaches in practice makes use of static ratios that determine the number of personnel or police cars based on the number of residents in a district or the number of calls for service over time (McCabe, 2012). While these static approaches are easy to handle, they are typically not able to provide reliable estimates that capture the heterogeneity and variability of police work (Wilson and Weiss, 2014). There is thus a general demand for more comprehensive approaches that model the effects of different calls for service on workloads and conduct capacity planning with respect to these relationships.

In other areas of application, such as logistics, staffing decisions in complex dynamic systems are often carried out by integrating simulation studies into capacity planning (see for instance Mason et al., 1998). The major advantage of such simulative analyses is that they are able to capture the interaction effects of different sources of stochastic influence and allow a study of the system's behaviour over time. Only recently, Zhang et al. (2012) demonstrated the superiority of simulation driven planning in the field of hospital resource planning when compared to a set of static ratio approaches quite similar to those used in police staffing. Nonetheless, reports of similarly advanced approaches in the field of policing are rare. Edleston and Bartlett (2012) are among the very few documented authors that use more advanced optimization techniques coupled with simulation analysis to support police staffing decisions.

In this work we will line out a simulation model that seeks to address the identified need for more comprehensive planning tools in policing. We study a major German metropolitan area that consists of 24 police districts that need to be equipped with an adequate number of police cars over the week. At the time of the project, resource allocation is carried out by a static ratio approach based on the average number of calls per district and hour thereby ignoring individual characteristics of different districts and the dynamic interactions in the arrival patterns of incoming calls. The major aim of the simulation model is to adequately capture these relationships to better support capacity decisions.

2 Data Analysis

One of the central challenges of police force planning is dealing with the considerable operational heterogeneity of calls for service that typically vary structurally over time and space. On the one hand, this makes deriving reliable estimates for capacity utilization much more difficult, on the other hand it typically leads to considerable variations in capacity demand over time and thus increases the complexity of an adequate

shift and fleet planning. In order to derive insights into the service structure, we therefore first carried out a comprehensive data analysis of more than 1.5 mio real-world calls for service, comprising information about the time and place of occurrence, call type, priority and number of assigned police cars over time. In addition to that, we conducted several workshops with police experts in order to obtain time estimates for all further service dependent tasks, in particular related to documentation and administrative work. Both analyses and their main results are explained in more detail in the following.

2.1 Analysis of Calls for Service

In a first step of the analysis, the call data was screened for incomplete and misreported data using both standard statistical outlier detection and expert analysis and depending on the extent either replaced by mean value estimates or removed from further analysis. Approximately, 5% of data entries were removed by this procedure. The remaining data was then analysed using means and variance analysis, which confirmed the following four core hypotheses:

- (1) Occurrence frequencies of calls for service vary heavily over time of day and police district
- (2) On scene resolution times vary heavily with respect to the type of call, but also albeit less distinctly with respect to place
- (3) Associated workload also varies heavily over time of day and police district yet characteristic workload profiles can be derived for each weekday and district that are stable over time
- (4) Police districts make extensive use of resource sharing in emergency response, such that police cars of a given district respond to calls for service in another district if no alternative is available

The analysis further revealed structural differences in occurrence of calls for service and on-scene resolution times between the warmer and the colder months of the year, which further results to systematically different workload profiles for summer and winter shifts.

2.2 Analysis of administrative work

The central information system that records data on calls for service does not cover any additional administrative tasks that are for instance required to document the on-site events or to file the necessary paperwork for law enforcement. Therefore, we used a Delphi method to determine these times depending on the type of police operation. Häder (2014) considers the classic Delphi method to be a comparatively, highly structured group communication process. Facts about which insecure and incomplete knowledge exists are judged by experts. The basic aspects of this method are group communication and the structuring of unknown information. The collected

information of the experts receives a higher qualification through the multi-level questioning. The classic Delphi process according to Webler et al. (1991) is characterized by a multi-step approach. At least four, but no more than five steps must be completed. The first step is the development of the questionnaire, in the second step the first survey of the experts, in the third step the evaluation by the research team and in the fourth step the second survey of the experts. Due to time and personnel constraints we chose a procedure where a questionnaire is delivered to experts in advance of and after one workshop. The process of our application of the Delphi method is depicted in Figure 1.

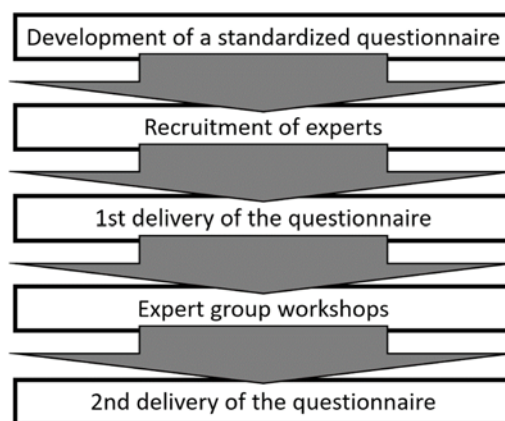


Figure 1: Applied Delphi method

The questionnaire was developed in order to request an estimate of the percentage share for the entire process production and post-processing per type of operation in addition to the function group. For the 48 most common types of operations, covering 85% of all missions, three questionnaires with 16 types of use were created. In order not to burden the experts inappropriately, everyone randomly received one of the three questionnaires. For each type of operation, three estimates of the further tasks should be made in minutes, for a task with:

- simple effort,
- average effort, and
- high effort.

This method is based on the three-point estimate in which experts give an optimistic, a pessimistic and a realistic estimate. This often determines the costs of the entire project in project groups. The advantage of this estimation is the simple and easy to understand application. As experts, 96 experienced police officers of four groups were selected from all police districts, each: a service group leader, a watch officer, one from the career sections 1 and 2. The experts were supposed neither to state their names nor to which district they belonged. The results showed coefficients of variation of 0.4 to 1.0. After the questionnaires had been evaluated, the four groups were invited to separate workshops. Each group discussed the consolidated average time

of their group for the three estimates (simple, average, and high effort) in four hours in the afternoon. After the discussion, the experts were questioned again in the same way as before. By this, the coefficients of variation could be reduced to 0.2 to 0.3.

3 Stochastic Process Models

In this section we describe how stochastic process models for workload estimation were derived on the basis of the conducted data analysis, as summarized in Figure 2. In a first step, calls for service were combined to appropriate reference classes whenever possible to reduce the number of necessary estimates in the following steps. Next we estimated occurrence probabilities from historic data over time and space and the time necessary to approach the site of the call. Finally, the distribution over workload profile of the call was determined as well as the time for administrative work.

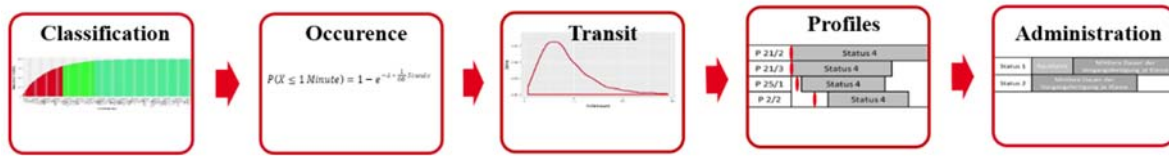


Figure 2: Process Model

3.1 Classification of calls for service

In order to reduce the complexity of the considered system, we first set out to reduce the number of reference classes of calls for service by conducting a Pareto analysis. For this purpose, all calls were ranked with respect to their total effect on workloads and then assigned to three distinct categories. The 37 calls that comprised more than 80 % of the workload were assigned to category ‘A’ and modeled individually. The next 32 calls that utilized another 15 % of the workload were assigned to category ‘B’ and the remaining calls to category ‘C’. Calls in category B were analyzed with respect to their characteristics and merged to classes of calls with similar profiles whenever possible. Calls in category C were subsumed under a single class due to their low impact on workloads. All in all, we were able to reduce the number of classes to a third of the total number of calls in this way (54 classes instead of 162 calls).

3.2 Occurrence model and transit estimation

As was established in the data analysis, relative frequencies of calls for service vary heavily over time and place. Occurrence probabilities were thus modelled as non-stationary Poisson processes and estimated separately for all districts and weekly hours.

In many of the less frequent calls for service relative occurrence rates were less than one per hour, so that sampling was conducted on the underlying binomial distribution using per minute approximations:

$$P(X \leq 1 \text{ minute}) = 1 - e^{(-\lambda/60)}$$

where X represents the time of the next occurrence and λ is the hourly arrival rate of the call.

Transit times of assigned police cars were estimated for each district individually to account for the considerable differences in size and traffic flows. We found that most transit times could be adequately approximated by lognormal distributions. Distribution parameters were estimated after conducting an additional outlier analysis that accounted for the observed shapes of distributions.

3.3 Capacity profiles and administrative work

Different calls for service can vary heavily with respect to average resolution times as well as the number of police cars assigned to the call. What is more, the dynamic nature of police work sometimes makes it necessary to further assign additional police cars to an ongoing call or to withdraw police cars that are not needed any further. Due to the extensive number of interaction effects; estimating these relationships and approximating them by stochastic distributions proved challenging and carries the additional risk of introducing structural biases that are not borne out in the data. We thus decided for a boot strapping approach that draws realistic capacity profiles for each reference class out of a set of observed calls for service. While this has the disadvantage that the simulation will not be able to generate call profiles that were not yet observed, it rules out the possibility of constructing unrealistic resolution dynamics. The extensive number of observations in the reference classes further make sure that the represented variability remains sufficiently high.

Administrative work was assigned to police staff that as mean estimates without considering the inherent real-world variability. Since the process model assumes that administrative work can be interrupted in case of emergency calls, the variability of the administrative time will not affect response times of critical calls anyway and thus mean estimates are sufficient for any long-term analysis.

4 Concept of the Simulation Model

The stochastic process model described in the previous section adequately captures the demand side. In order to assess the system performance accurately in light of the demand, it is further necessary to model how calls for service are handled by the system. For this purpose, a discrete event simulation (DES) has been developed based on queue modelling with spatial and temporal differentiation. This allows determin-

ing the burden put on the system according to current capacity plans and further allows deriving hints with respect to performance-based capacity adjustment. Thus, workload-appropriate capacity plans can be suggested by leveraging the gained insights of the data analysis in the simulation.

The Stochastic Event Generator in Figure 3 builds upon the developed process model and is the starting point for the simulation. Based on the past data it generates N weekly load profiles in minute resolution. These provide the discrete demand events as calls for service in the simulation. To satisfy the demand in the simulation, capacity plans and respective shift plans of all police districts provide the supply side in form of police cars. Demand and supply are represented as grey input data blocks for the DES model in Figure 3.

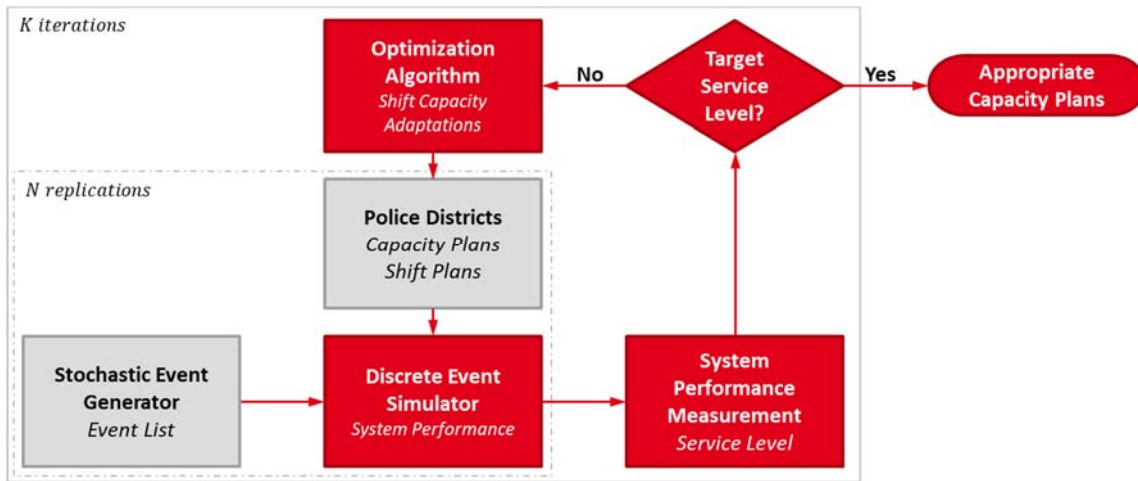


Figure 3: Overview of the blocks and processes of the higher-level simulation and planning task

A weekly load profile comprises about 9000 missions. For each mission the data of the occurrence (district, time, day of the week, month), the type (call for service, police car requirement, priority) and the operation (travel time, duration of operation on-site, administrative work) are saved as attributes and considered in the simulation. On the supply side, for all districts capacity plan data (day, time, shift, number of police cars) is used in minute resolution. Additionally, for each district an individually ordered list of backup districts reproduce the identified resource sharing patterns in the simulation.

With these data sets and implemented logic, the DES model tries to serve the demand with the given capacity. In the process the system performance for each of the N replications, which represent different realizations of load profiles, is measured and service levels for all call priorities are determined. If service level targets are not met, the capacities can be (spatially and temporally) adapted with respect to observed performance. With the resulting new capacity plans, the simulation is repeated in the next iteration. This process continues until, after K iterations of capacity adjustments

or until the target service levels are reached and thus adequate capacity plans have been created.

5 Discussion of Results and Future Work

The simulation model was validated against real data comprising three weeks of recorded calls and managed to reproduce all main measures of system performance (response times, calls not answered within x minutes, capacity exchange between districts) with high reliability. We further conducted separate workload analyses for representative summer and winter months and were able to show that prior capacity plans that were generated by a static ratio approach systematically fail to capture the diversity between districts and times of day, whereas the simulation approach does provide robust insights into the diverging workload structure.

In the next phase, we seek to employ the simulation model for deriving adequate capacity plans that account for the aforementioned structural differences. It is further planned to implement staffing changes on the basis of these insights, in order to further test the generated model predictions of the system performance against the real dynamics in practice.

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