Discrete-Event Simulation Modeling for Housing of Homeless Populations

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Abstract

The San Francisco Bay Area has experienced a rapid increase in the homeless population in the past decade. There is an increasing need for quantitative analysis to determine how to increase the amount of housing in order to decrease the number of unsheltered people. Noting that the shortage of housing through the homeless system can modeled as a queue, we propose a discrete-event simulation to model the long-term flow of people through the continuum of care. The model takes as input the rate of building for housing and shelter each year, and delivers as output the predicted number of people housed, sheltered, or unsheltered in the system. We worked with a team of stakeholders to analyze the data and processes for Alameda County in California and use this information to build and calibrate two simulation models. One model looks at aggregate need for housing, while the other differentiates the needs of the population into eight different types of specific need. The model suggests that a large investment in permanent housing and an initial ramp up of shelter is needed to eliminate the current unsheltered population and accommodate future inflow to the system.

1 Introduction

Many parts of the US have faced housing crises, where rising home and rent prices have led to more people unable to afford housing. The San Francisco Bay Area has been notably affected. Alameda County, located east of San Francisco, includes the cities of Oakland and Berkeley and has a population of approximately 1.7 million. This county has faced rapidly increasing numbers of homeless persons in the past decade with recent estimates of approximately 13,000 households currently in the homeless system. The county has devoted a number of resources to try to increase housing and shelter, which are defined as the following. Housing refers to a permanent or semi-permanent solution that results in someone being housed successfully, though they may still in the system or using county resources. Shelter refers to temporary accommodations that may meet some needs until a permanent housing solution becomes available. The queue for both housing and shelter consists of a large number of people who are unsheltered due to a lack of space in the system. In the Bay area, it is this recent increase in the unsheltered population that has led to even higher levels of concern. The commitment from the community to solving this crisis has led to a number of new proposed solutions, and quantitative methods are critical to evaluating the potential effectiveness of these solutions.

Our goal in this work is to introduce discrete-event simulation as a method for modeling the flow of people through the homeless system and predicting the effects of investment into housing on the unsheltered population. Discrete-event simulation is a key tool for modeling the flow of entities through a system with constrained resources. The support system for homeless persons involves managing the flow of people through shelters and housing resources over time. Discrete-event simulation is also easily able to incorporate randomness in the arrival rate of people to the system, or uncertainty in the length of time they will occupy a particular housing resource. To the best of our knowledge, this study is the first approach that uses discrete-event simulation to model the flow of people through an entire housing and shelter system as a queue.

We identify some of the key aspects of this queueing problem. The primary resource is housing, which is in limited supply due to limited space and high costs in terms of time and money to build new units. Additionally, turnover in housing units is low because it is designed to provide a permanent place for people to stay. The lack of resources to build at a rate fast enough to keep up with new additions to the homeless population is one reason for the current bottlenecks in the system. A secondary resource is emergency shelter, which is designed to provide a temporary place to stay until a housing unit becomes available. While the intent is for people to stay in shelter for weeks or at most a few months while permanent housing is being arranged, in reality people may stay far longer due to the lack of housing downstream. The shortage of housing and shelter has led to a large queue of unsheltered people who face limited options. The system can be classified as unstable from a queueing standpoint.

The objective of this research is to build a simulation model to test different investment policy scenarios subject to uncertainty in the system. Policymakers must decide how much housing and shelter to build given limited resources and pressure to alleviate the suffering of the unsheltered population. It is clear that levels of shelter must be increased in the short term to reduce the unsheltered population, but in the long run the goal is to have most of the resources invested in housing and have only minimal necessary shelter available as a backstop when housing isn't immediately available. One idea is to start with a surge increase of shelter to reduce the unsheltered population, and once housing levels catch up to current need, convert excess shelter to permanent housing.

There are many desired objectives, but one goal is referred to as "functional zero", when people only require intervention through the system infrequently and for a short period of time until permanent housing can be found. This is in contrast with the current state of affairs, where it can take years from the time of entry into the system to the time which obtain permanent housing is obtained. Thus, the goal is not only to bring the number of unsheltered down to zero, but to keep the overflow from housing into emergency shelter low enough that the time spent in shelter is limited.

An additional challenge is communicating proposed investment options with decision makers. Given the high costs associated with solving the homeless crisis, accurate models are needed to justify high levels of investment in housing. Policymakers may have other priorities for use of limited funds, or may balk at the high cost of building permanent housing. Constituents may prefer to shelter people as quickly as possible to reduce the number of unsheltered people living on the streets. However, undesirable shelter conditions may deter people from entering shelter, especially if there is no clear or timely pathway to housing. Focusing on building housing is more costly and may provide a better long term solution for more homeless people in the long term, but may be a difficult solution to sell to constituents. An accurate simulation model could show the long-term effects of investment in housing on the overall homeless population to aid in decisionmaking.

This paper presents two simulation models developed in conjunction with the Alameda County Office of Homeless Care and Coordination. Section 2 outlines related literature, while Section 3 details the data collection efforts used to calibrate the simulation models. Section 4 describes the first simulation model which aggregate all types of housing into a single category, while Section 5 presents a detailed pathway model that includes eight different pathways through the system. Results of the simulation models are presented in both Section 4 and Section 5. Section 6 contains concluding thoughts and future work.

2 Literature Review

The combination of simulation and optimization has been widely used to address the challenges associated with complex societal problems requiring local government coordination (i.e, planning emergency response infrastructure (Lee et al. 2009)). Simulation can often be used to test the effects of potential interventions in healthcare and human systems, for example, Arenas et al. (2017) studies medical clinics and Slaugh et al. (2016) models an adoption matching process. Additionally, the problems for constructing and allocating affordable housing has been studied under community-based operations research (Johnson and Smilowitz 2007).

There has been much work to develop analytical and statistical models for various aspects of the homeless population. Patlolla et al. (2004) use an agent-based model for tuberculosis outbreaks in shelters, while Higgs et al. (2007) develop spatial models for tuberculosis outbreaks among the San Francisco homeless population. Brown et al. (2019) use a regression model to identify trajectories of increased functional impairment among the homeless in Oakland, CA. Of particular interest in Oakland is research into the reasons why people of color experience homelessness at disproportional rate. Paul Jr et al. (2020) surveyed people in Oakland to assess levels of overt racism and structural racism in the process of obtaining housing.

Ingle et al. (2021) create a model to project the number of rooms needed to isolate and house members of the homeless population during a COVID-19 surge in Austin, TX. Developing good estimates of the needs of the homeless population during changing conditions is crucial to resource planning, and it is important to take into account the changes in arrivals to the system during the pandemic. El Hage et al. (2021) develop a discrete-event simulation in Simio to model the process of COVID-19 testing and determine where potential improvements could be made to increase testing capacity. The effect of COVID-19 outbreaks in homeless shelters was also studied in Chapman et al. (2021), which suggests a need for non-congregate shelter as opposed to high density congregate shelter where preventative measures to prevent an outbreak may be unsuccessful.

Models for matching homeless individuals with housing have been studied in great detail. For example, Khayyatkhoshnevis et al. (2020) consider the quality of a match between an individual and housing provider, and solve an optimization problem to find the best matching using a number of heuristic methods. The decision on the number and type of options offered in social service settings was analyzed in Arora et al. (2021), whereby it is sometimes optimal to offer a less diverse set of services and higher advisory levels to ensure the people get matched with the correct service levels.

Discrete-event simulation was used in Reynolds et al. (2010) to model the flow of homeless persons through a health clinic in Lexington, KY. Various staffing levels and random processing distributions were used to estimate the effect on waiting times in the queue. Simulation is also used in Yadav et al. (2016) to assess the quality of a partially observable Markov decision process to optimize the choice of sequential interventions to help homeless youths using social networks. Like some of the work mentioned above, our work uses discrete-event simulation, but models the overall flow of people through the entire system over a long-term period of years, rather than focusing on a particular clinic or shelter in the short term.

3 Model Calibration

To the best of our knowledge, discrete-event simulation has not been used to model the flow of people through a homeless care system including the longer-term process of placement in housing. Queueing models provide a natural framework for analyzing the shortage of housing which is causing a large number of people to be unsheltered. Given the relative complexities and limitations of moving people through the system, discrete-event simulation is an ideal tool to model this complex process. We build two discrete-event simulation models using Simio simulation software to incorporate detailed data about the system.

The continuum of care (CoC) describes the process from the time a person enters the county system requesting assistance, to the time they exit the system to housing that is not part of the county housing program. While there are many administrative steps involved in entering the system and receiving care, we focus our model on the major housing and shelter stages which are the primary bottlenecks in the system. In Alameda County, the system is unstable from a queueing perspective, meaning that the rate of inflow to the system is faster than the rate of outflow to external housing. Thus, standard queueing approximations will not necessarily hold, and simulation will allow for the flexibility to model the resulting crisis due to this instability.

Simulation also allows for easy scenario analysis to model different configurations of investment policies to test the effects of varying rates of building shelter and housing.

The authors conducted a study of the data in the system in conjunction with members of Alameda County's Office of Homeless Care and Coordination, as well as other nonprofit leaders and local stakeholders. Data was pulled from HMIS (Homeless Management Information System) to obtain population estimates from different regions. Key data values of interest include the population and arrival rates to the CoC, housing and shelter inventory levels, and rates of returns to the system. This data was used in a systems modeling study to estimate the yearly inflow/outflow through the system. This systems model was constructed by experts with background analyzing CoCs, and we use this model to calibrate model logic in the simulation study.

The point-in-time (PIT) count is an estimate of the number of homeless people conducted over a single night. The PIT count is hard to obtain and can be collected using grid searches of cities, or telephone surveys (Agans et al. 2014). PIT counts are critical to calibrating our model to estimate the number of people in the system at the start of the simulation. Metraux et al. (2016) develop an alternative method for estimating the number of homeless persons looking at data from deceased persons. This method estimates the number of hidden homeless populations, who may have different fundamental properties than those counted under traditional methods. Oakland-Berkeley-Alameda County CoC (2020) analyzed the data in Alameda County to determine the extent to which racial minorities are disproportionately represented in the homeless system, and the data analysis from this report helped inform the parameters of our model.

Of those that leave the housing system, approximately 17% will return the system in two years, further increasing the inflow. In Alameda County, the current arrival rate of new people to the system as estimated from the most recent HMIS data is approximately 3,500/year. This rate has been particularly high in Alameda County due to rapidly increasing housing prices. The data study assumed a slight increase in new arrivals to the system in the first two years followed by a stabilization and decline in arrivals in the last years due to proposed prevention methods. In the simulation model, we will use a non-homogeneous Poisson process to model the changing arrival rate over time. Additionally, while there was much effort to analyze data relating to households with children, we focus this model on adult-only households since those comprise the vast majority of homeless households in Alameda County.

The COVID-19 pandemic led to a surge in homelessness in part because of job losses and economic conditions, but also because shelters could no longer operate at full capacity. However, data collection procedures also stopped during the pandemic making it hard to count the number of unsheltered. The usual PIT count that covers the region to count the number of unsheltered was delayed, thus the population numbers available are approximate. On a positive note, in California, the pandemic resulted in Project Roomkey, where vacant hotels and facilities were used to house and isolate homeless persons at risk for COVID-19. Zeger (2021) analyzes the effect of Project Roomkey and highlights that it was successful in sheltering thousands of people and moving them into permanent housing at much higher rates than standard congregate shelters.

The results of this data collection effort led to calibration of two simulation models. The first simulation model presented in Section 4 studies the aggregate flow through Alameda County without distinguishing between different types of housing needs. The second simulation model in Section 5 incorporates details about different pathways that can be taken through the system based on varying individual needs. All simulation results and code used to generate the plots in this paper are available online at `https://faculty.nps.edu/dsingham`.

4 Aggregate Model

We first build a model of the aggregate system which considers all types of housing as a single type of resource. This simpler model will enable us to assess in general terms how much housing is needed to eliminate the unsheltered population over the next five years. Figure 1 shows the simplest possible layout. People arrive to the system seeking housing. If housing isn't available, they attempt to stay in shelter. If shelter is not available, then they wait in the queue for shelter. This queue represents the current unsheltered population. Between shelter and housing we do not model a queue, because people wait for housing to become available before leaving shelter. Thus, the shelter server is often "blocked" because they cannot release people if there is no housing available for them. In reality, people may leave shelter for various reasons and return to the homeless population, but their spot would immediately be filled anyway by someone else given the current high levels of homelessness.

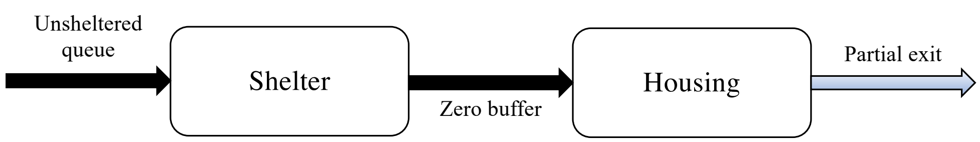

Figure 1: Aggregate housing and shelter system. The blue arrow exiting housing means that not everyone will exit, as some people will stay permanently in the county housing system.

The shelter resource is not a typical server because rather than each person having a specified time in the server, people wait until a spot in housing opens up before leaving. Similarly, the housing server is not a typical server because most people stay in the system indefinitely. A successful housing placement often results in a permanent accommodation. We model the time spent in the housing server as a random triangular distribution with minimum 0, mode 6 years, and maximum 8 years to model fairly long stays in this server. As mentioned in Section 3, people may also return the system after exiting if they return to homelessness. This makes it even more difficult to obtain stability (in the queueing sense) because the outflow from the housing server is much lower than the inflow to the system.

Thus, one potential solution is to continually increase the amount of housing to accommodate increased demand and limited outflow. The objective is to increase overall shelter and housing rates to decrease the unsheltered population. In the ideal long term case, people would primarily be housed in permanent housing, and minimal shelter would exist to handle the incidental short term backlog as people wait for housing. However, given the large number of unsheltered people in Alameda County, it may make sense to have a surge of shelter constructed to temporarily give people a place to stay while long-term housing is being built. It may be possible to then convert the shelter to permanent housing as the unsheltered population decreases.

We the effects of various investment policies on the system. These types of policies may not always be feasible and are subject to budgetary constraints, but the simulation model can be used to determine the corresponding effects on the unsheltered and homeless. The team at the Office of Homeless Care and Coordination used systems modeling to develop a plan that would reach functional zero in five years through heavy investment in housing. Table 1 shows rounded values of the proposed plan to build shelter and housing over a five year period. Shelter would increase in initial years, but then decrease over time as it is transitioned to permanent housing, while housing increases steadily.

Table 1: Approximate investment plan developed by the focus group. Units are total numbers of adults accommodated at the beginning of the year.

Year	Total Shelter	Total Housing
2022	1,500	4,000
2023	2,500	6,000
2024	3,200	9,600
2025	3,000	13,600
2026	1,600	19,300
2027	1,200	24,000

Figure 2 shows the results of two possible investment policies using the aggregate simulation model. These results come from a single replication of each simulation so are representative of a possible reasonable trajectory, but not the estimated average trajectory. The left plot shows a scenario using the proposed plan in Table 1. With heavy investment in housing, we see a steep increase in occupied housing over the five year period. The amount of shelter available ramps up initially, then declines in later year. Because of the heavy investment in housing, the unsheltered population decreases over time and eventually the goal of functional zero is met.

The right plot of Figure 2 shows an alternate simulation where there is only 70% investment in housing compared to the values in Table 1. There is some additional ramp up of shelter, and no decline or conversion from shelter in later year. We see that such a plan is able to stabilize the number of unsheltered people, but not able to bring it down to zero. Thus, without rapid increases in housing and shelter to deal with current and future unmet need, functional zero is unlikely to be achieved within five years.

The aggregate model can be used to get a sense of the overall volume of new housing needed to meet the long term goals of Alameda County, and we see that approximately 24,000 units of housing are needed if the current inflow rate to the system remains the same. Next, we present the

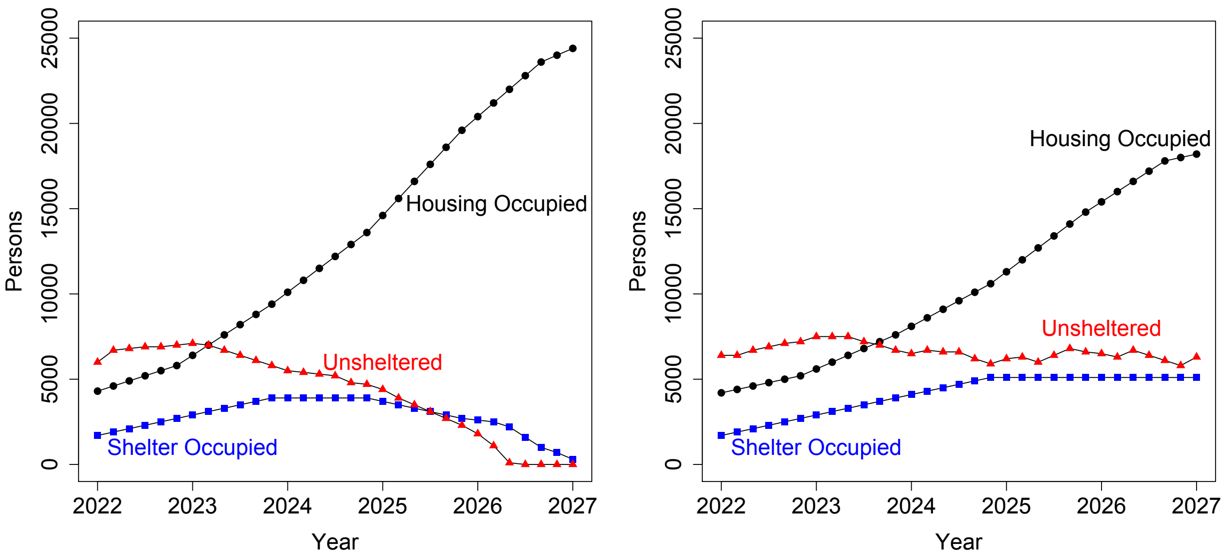

Figure 2: Left: Aggregate simulation results using build plan in Table 1. Right: modified plan with 70% investment in housing compared to Table 1, and no decline in shelter. Both plots are the result of a single replication of the simulation model.

detailed model which differentiates individual pathways through the system and models separate queues for each type of housing. This analysis can inform the allocation of resources towards certain types of housing options.

5 Detailed Pathway Model

While the aggregate model gives some indication of total building rates needed for housing and shelter, it does not take into account the nuanced pathways taken by different types of people through the system. People arriving to the CoC have very different needs. Some may require permanent housing with medical and social services assistance, while others may simply need additional funds to stay in their current unit. Figure 3 shows a simplified layout of the pathways through the system in Alameda County. There are some pathways that do not involve stays in emergency shelter. For example, youth transitional housing is a separate system with relatively high levels of funding in Alameda County. Rapid resolution (RR-short) housing supports those who need short term financial assistance to afford their rent, but do not need a place to stay. Rapid resolution and self-resolvers (SR) (the blue servers) involve minimal intervention from the system, but self-resolvers may require shelter while waiting for a their new accommodations to become available.

Rapid rehousing (RRH) (green servers) helps those who may be able to find a new place quickly with assistance from the county, perhaps through a subsidy or through a connection to a known vacancy. Some people in this category require a stay in emergency shelter, while others may not

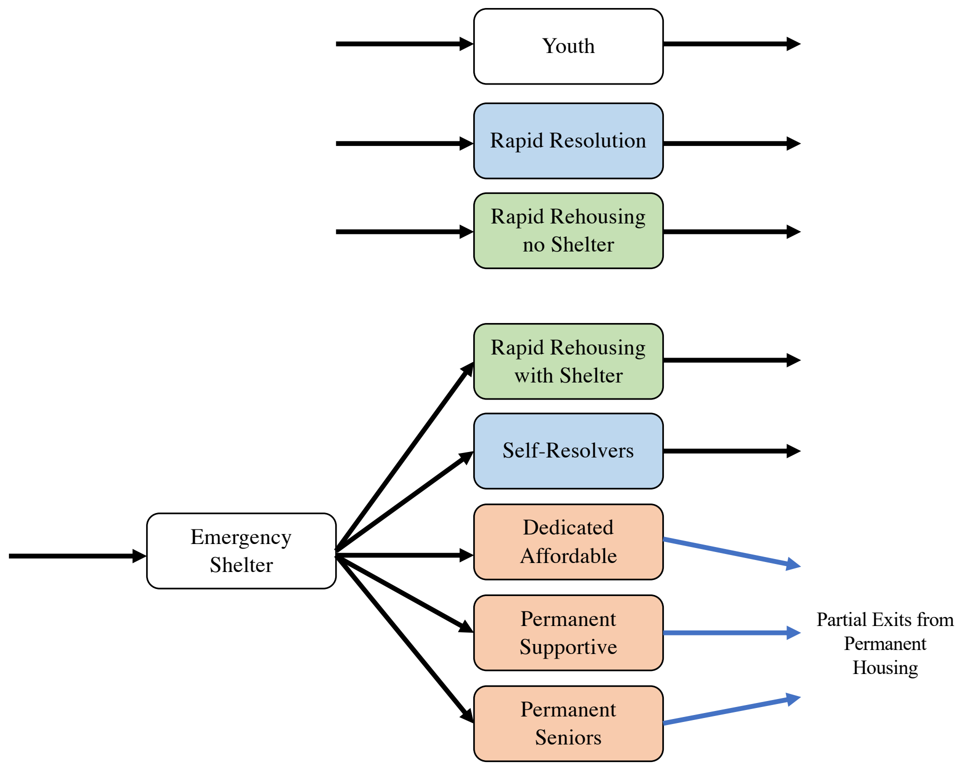

Figure 3: Detailed model of pathways through the system.

but may need a subsidy (RR-long), so this category is split into two servers. Finally, the orange servers are those requiring the most resources for the system as they are the highest cost and house people for long periods of time. These pathways are for those who require permanent or long-term solutions. Dedicated affordable (DA) housing is designed to be priced so that is affordable and not subject to Bay Area market fluctuations. Permanent supportive housing (PSH) is for those with physical or mental disabilities who need social services in conjunction with their housing, while permanent supportive housing for senior citizens (PSH-S) is allocated a separate pathway. The lack of housing in this orange category is a major part of the current crisis because this type of investment is costly and time consuming and currently has high demand. Additionally, there is low turnover in this category. Most people may not exit the system for many years, and some may stay permanently.

The detailed model has many enhancements from the aggregate model to account for the differences in pathways. The different types of arrivals each have their own arrival rate proportional to their representation in the system. Each type of resource has a unique distribution for the amount of time a person occupies the housing. For example, permanent supportive housing and dedicated affordable housing could be occupied by the same person for years, while rapid resolution usually provides financial support on the order of months. Details on each type of pathway are included in Table 2.

Table 2: Pathway population details including proportion of population, *average* time in shelter, and *average* time in housing.

Pathway	Prop. of pop.	Shelter Time	Housing Time
Youth Transitional (Youth)	2%	N/A	1 year
Rapid Resolution - Long term (RR-Long)	10%	N/A	5 years
Rapid Resolution - Short term (RR-Short)	10%	N/A	3 mos
Rapid Rehousing (RRH)	15%	Until hsng avail	6 years
Self Resolution (SR)	10%	5 mos	N/A
Dedicated Affordable (DA)	28%	Until hsng avail	5 years
Permanent Supportive Hsng (PSH)	15%	Until hsng avail	5 years
Permanent Supportive Hsng, Seniors (PSH-Seniors)	10%	Until hsng avail	5 years

Additionally, each type of arrival to the system is assigned a priority. Emergency shelter space is often limited, so priority is given to those with the most physical need like PSH and PSH-Seniors. Each type of arrival also has its own need for shelter. Some people do not need any shelter, some need it for a limited amount of time, while others may need to stay in shelter indefinitely until an exit to housing becomes available. As in the aggregate model, the shelter server may often be blocked no downstream housing is available. People who may require permanent supportive housing will wait in shelter indefinitely until housing is available, and this prevents those who may only need temporary shelter for a few months (or even weeks) from obtaining shelter.

In the detailed model, we take into account the number of resources available for each pathway over time. The proposed investment policies will increase the number of resources available each year attempting to match the proportions of relative need in the system. The overall intention is to reduce the number of unsheltered people, and eventually reducing even the amount of emergency shelter needed. The emergency shelter serves as a backstop for those who are unable to access housing, but given current limitations on shelter accommodations there still are thousands of unsheltered people in the county. Similar to the aggregate model, as housing investment increases we can unblock the shelter through exits to housing.

Table 3 contains one such investment policy proposed by the systems modeling group. We call this policy IP100 and this will form the baseline for generating alternate policies. It attempts to increase resources proportionally to the approximate population of people requiring the pathway. As in the aggregate model, the total shelter will increase initially to decrease the number of unsheltered people, but will decrease in later years as more housing becomes available.

We run 100 replications of the detailed model using the investment policy in Table 3 to see the effect of parameter uncertainty on the overall results of the investment policy. Figure 4 shows parallel boxplots for each year representing the uncertainty in the predicted values of the amount of housing occupied, the amount of shelter occupied, and the number of unsheltered people. Because the system is resource constrained, there is not much uncertainty relative to the overall number of people in the system. Housing occupied will generally be at the limit of housing available, though at the end of the five year period we see a possible drop in housing occupied due to exits from the

Table 3: Investment Policy (IP100) suggested by the system modeling team to match proportional need. Values are total units to exist by the end of the year (not incremental new units).

Year	Shelter	Youth	RR-Long	RR-Short	RRH	DA	PSH	PSH-S
2023	2,652	104	677	130	1,120	1,459	3,351	521
2024	3.221	121	1459	152	1,305	3,085	4,054	1,086
2025	2,984	138	2,260	173	1,488	4,869	4,837	1,691
2026	1,652	195	3,416	244	2,100	7,359	6,013	2,532
2027	1,253	173	4,368	216	1,857	9,411	6,914	3,194

system. Shelter occupied is also at its limit for the first few years, though once housing increases it drops drastically and mainly serves as a backstop when housing is unavailable for a particular pathway. We see some uncertainty in the number of unsheltered, as this is the combined number in the queue for all the pathways. We expect there to be some variability in the number of unsheltered until the system reaches functional zero, in which case the unsheltered population should go to zero.

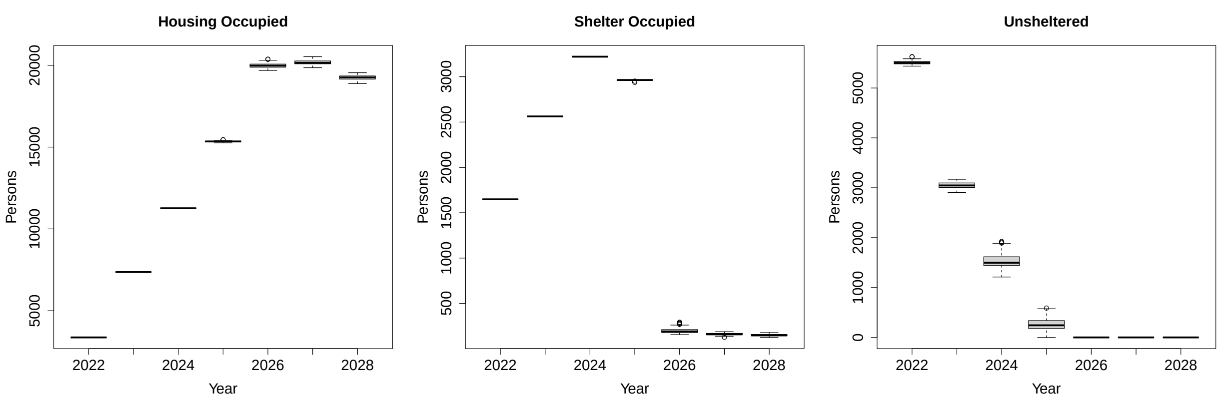

Figure 4: Boxplots showing uncertainty in simulation trajectories for housing occupied, shelter occupied, and the unsheltered population for the investment policy IP100 in Table 3.

The proposed investment plan in Table 3 costs an estimated $2.5 billion because of the long term costs of building quality housing that supports the needs of the population. Building units of dedicated affordable housing or permanent supportive housing is substantially more expensive than providing subsidies to keep people in their current homes. The detailed model allows us to differentiate between types of housing allocation policies and see the effect of prioritizing different types of need. Figure 5 shows the amount of unmet need for each pathway over time by averaging over 100 independent replications of the detailed model using the investment policy IP100. Unmet need is defined as the number in the queue plus the number in emergency shelter awaiting housing for each pathway. Essentially this is the number of people who have not reached the final stage of housing whereby they would be marked as a successful completion.

We see the unmet need decreases over time and for the most part goes to zero after four years. Both youth and self-resolvers will continue to have unmet need in the system as they arrive and

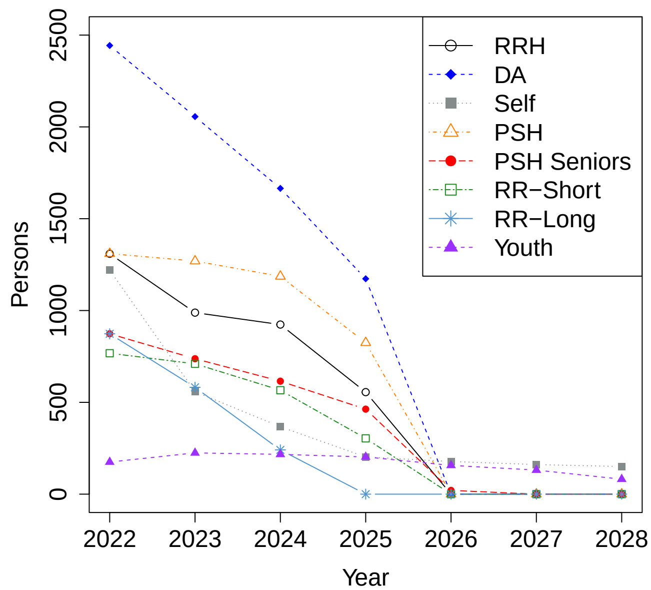

Figure 5: Unmet need for each pathway, each point averaged over 100 independent stochastic replications, using the investment policy in Table 3 (IP100).

may find constraints on housing and emergency shelter as the system reaches a steady state. The investment policy in Table 3 is based on allocating proportionally to population needs, so fewer resources are initially allocated to youth transitional housing. Self-resolvers don't require housing investment, just shelter, so there will always be some self-resolvers in shelter while waiting for their resolution.

To see how sensitive these trajectories are to the investment policy in Table 3, we test what would occur if investment happened at the slower rates of 90% and 80% of the total units built in IP100 (call these policies IP90 and IP80). These results are plotted in Figure 6. By scaling down the number of units available, we see that it takes longer to reach functional zero and the amount of unmet need is understandably higher in earlier years. In the right plot of IP80 using 80% of IP100, the number of people needing dedicated affordable housing is particularly high and does not decrease for many years. The number of people needing rapid rehousing also does not appear to approach zero in the short term.

This analysis encourages us to formulate an alternative investment policy that allocates more resources to the pathways with the largest queues, while decreasing resources to those with lower queues that reach zero more quickly. This tests the sensitivity of IP100 to small changes in the resource allocations. We attempt to stay around the $2.5 billion cost associated with the investment policy in Table 3 while finding an allocation that decreases the overall numbers in the queue in early years. Consider increasing the investment in rapid rehousing, dedicated affordable housing, and permanent supportive housing by 10% of the values in Table 3. These are the pathways with

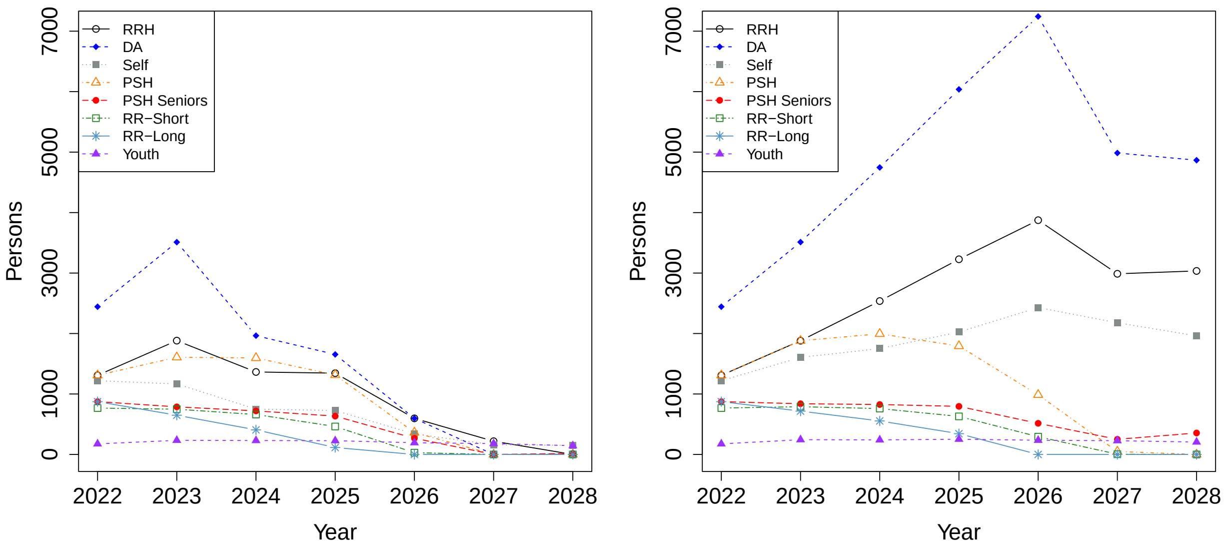

Figure 6: Left: Unmet need using the investment policy of 90% of that in Table 3 using IP90. Right: Unmet need using the investment policy of 80% of that in Table 3 using IP80.

the longest queues, but also have fairly high costs per unit. To reduce the overall costs down to \$2.5 billion, we reduce the number of planned units for rapid resolution (RR-long and RR-short), youth housing, and permanent supportive housing for seniors to 80% of those of in IP100 in Table 3. Call this investment policy IP1080.

The left plot of Figure 7 shows the results of investment policy IP1080. The rate of decrease in unmet need for DA is faster than in IP100, but the decrease in resources allocated to other areas means that many of the pathways do not go to zero. We can also consider increasing investment in rapid rehousing, dedicated affordable housing, and permanent supportive housing by only 5% while decreasing investment in planned units for rapid resolution (RR-long and RR-short), youth housing, and permanent supportive housing for seniors to 90% of the original levels in IP100. The result of this policy (IP0590) is shown in the right plot of Figure 7, which does a slightly better job of bringing PSH-Senior and and RR-short down to zero earlier.

To summarize the policies tested, Table 4 lists the properties of each policy, as well as the cost and total number of people with an unmet need each year. This total unmet need sums over the values for each pathway in the prior figures. The first three policies have similar costs but different allocations relative to IP100. Allocating more investment to rapid rehousing, dedicated affordable housing, and permanent supportive housing does decrease the total amount of people with unmet need in the early years in IP1080 and IP0590 compared to IP100, but we end up with more people left in the system in later years due to underinvestment in other pathways. The investment plans IP90 and IP80 are less expensive due to the overall smaller investment levels, but end up with more people left in the system. In particular, IP80 is not really enough to bring the unmet need down

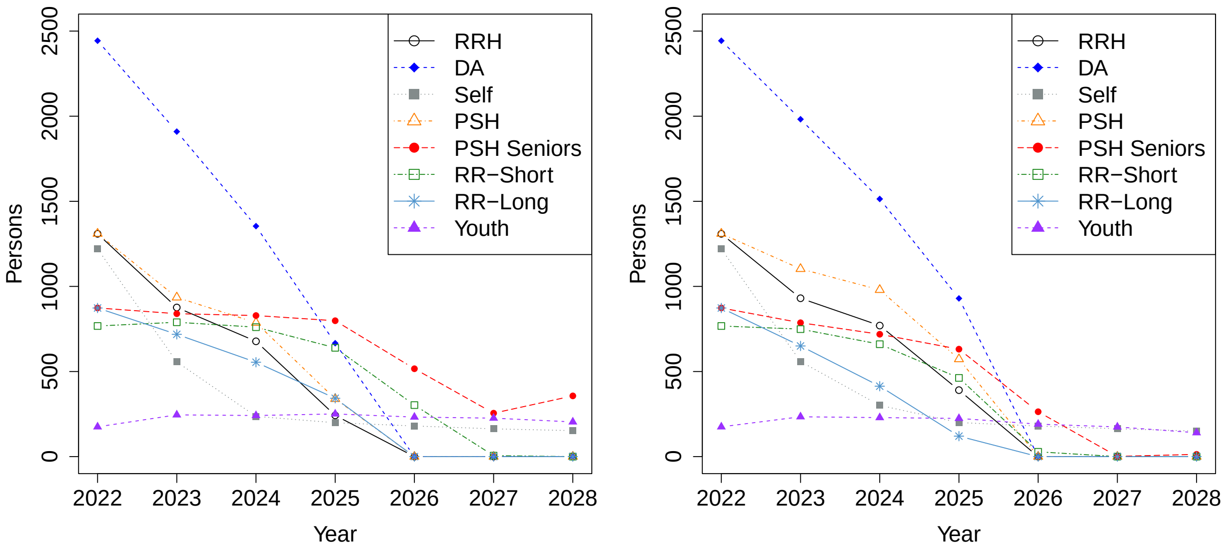

Figure 7: Left: Unmet need using investment policy IP1080 which increased investment to some pathways by 110% and decreased others to 80% of IP100. Right: Unmet need using investment policy IP0590 which increased investment to some pathways by 105% and decreased others to 90% of IP100.

to manageable levels. However, all these policies assume the rate of arrivals remain approximately constant to the system over the five years (subject to non-homogeneous Poisson fluctuations). If prevention was able to significantly reduce the number of people emerging as homeless, then perhaps significant costs could be saved if less housing was needed in later years.

Table 4: Summary of policy costs and total unmet need.

Policy Name	Scale Factors (Up/down)	Cost (millions)	Total Unmet Need (Persons) 2023	2024	2025	2026	2027	2028
IP100	1.00	\$2.46	7,125	5,780	3,725	354	292	231
IP1080	1.10/0.80	\$2.51	6,870	5,440	3,478	1,231	650	713
IP0590	1.05/0.90	\$2.49	6,994	5,587	3,531	662	339	303
IP90	0.90	\$2.23	10,584	7,693	6,480	2,386	561	317
IP80	0.80	\$2.00	11,467	13,409	15,103	15,575	10,681	10,424

6 Conclusion

We construct two simulation models for the flow of people through Alameda County's continuum of care system. The models incorporate data input estimates and proposed investment policies to predict the number of people in the system over time needing housing and shelter. The first model treats all pathways through the system as homogeneous to estimate the total amount of housing and shelter needed over time. The second model differentiates between the various needs and pathways through the system, and allows for testing different investment allocation policies. Overall, it is clear that a substantial increase in new housing is needed both to address the current number of unsheltered people, and to manage future inflow of people to the system. An increase in shelter would help mitigate some of the suffering faced by the unsheltered population, but without new exits to housing, shelter alone does not result in a long term solution. In particular, investment in longer-term solutions such as dedicated affordable housing and permanent supportive housing is needed.

Estimates of future inflow to the system remain highly uncertain. There has been a rapid rise in homelessness in recent years, and if this rate of arrivals continues to be high, current resources will be hugely inadequate. But should this rate decrease, future work would be able to easily recalibrate the simulation model to determine new levels of housing needed. The current study focused on attempting to determine how to reach functional zero in five years, but did not take into account external inputs on actual costs or building constraints. Even if it is optimal to invest in high levels of permanent housing, it could take years for new housing to be fully constructed. Future work will incorporate feedback from stakeholders on what building rates are feasible to determine new investment allocation strategies under budgetary constraints. The simulation model can be easily adapted to work with any investment policy, and can incorporate new pathways as needed. We anticipate many potential innovations in this space.

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References

Robert P Agans, Malcolm T Jefferson, James M Bowling, Donglin Zeng, Jenny Yang, and Mark Silverbush. Enumerating the Hidden Homeless: Strategies to Estimate the Homeless Gone Missing From a Point-in-Time Count. *Journal of Official Statistics (JOS)*, 30(2), 2014.

Daniel J Arenas, Lanair A Lett, Heather Klusaritz, and Anne M Teitelman. A Monte Carlo Simulation Approach for Estimating the Health and Economic Impact of Interventions Provided at a Student-Run Clinic. *PLOS One*, 12(12):e0189718, 2017.

Priyank Arora, Morvarid Rahmani, and Karthik Ramachandran. Doing Less to do More? Optimal Service Portfolio of Non-Profits that Serve Distressed Individuals. *Manufacturing & Service Operations Management*, 2021.

Rebecca T Brown, David Guzman, Lauren M Kaplan, Claudia Ponath, Christopher T Lee, and Margot B Kushel. Trajectories of Functional Impairment in Homeless Older Adults: Results from the HOPE HOME Study. *PLOS One*, 14(8):e0221020, 2019.

Lloyd AC Chapman, Margot Kushel, Sarah N Cox, Ashley Scarborough, Caroline Cawley, Trang Q Nguyen, Isabel Rodriguez-Barraquer, Bryan Greenhouse, Elizabeth Imbert, and Nathan C Lo. Comparison of Infection Control Strategies to Reduce COVID-19 Outbreaks in Homeless Shelters in the United States: a Simulation Study. *BMC Medicine*, 19(1):1–13, 2021.

Jad El Hage, Patti Gravitt, Jacques Ravel, Nadia Lahrichi, and Erica Gralla. Supporting Scale-up of COVID-19 RT-PCR Testing Processes with Discrete Event Simulation. *PLOS One*, 16(7):e0255214, 2021.

Brandon W Higgs, Mojdeh Mohtashemi, Jennifer Grinsdale, and L Masae Kawamura. Early Detection of Tuberculosis Outbreaks Among the San Francisco Homeless: Trade-offs Between Spatial Resolution and Temporal Scale. *PLOS One*, 2(12):e1284, 2007.

Tanvi A Ingle, Maike Morrison, Xutong Wang, Timothy Mercer, Vella Karman, Spencer Fox, and Lauren Ancel Meyers. Projecting COVID-19 Isolation Bed Requirements for People Experiencing Homelessness. *PLOS One*, 16(5):e0251153, 2021.

Michael P Johnson and Karen Smilowitz. Community-Based Operations Research. In *OR Tools and Applications: Glimpses of Future Technologies*, pages 102–123. INFORMS, 2007.

Pedram Khayyatkhoshnevis, Salimur Choudhury, Eric Latimer, and Vijay Mago. Smart City Response to Homelessness. *IEEE Access*, 8:11380–11392, 2020.

Eva K Lee, Chien-Hung Chen, Ferdinand Pietz, and Bernard Benecke. Modeling and Optimizing the Public-Health Infrastructure for Emergency Response. *Interfaces*, 39(5):476–490, 2009.

Stephen Metraux, Janna Manjelievskaia, Dan Treglia, Roy Hoffman, Dennis P Culhane, and Bon S Ku. Posthumously Assessing a Homeless Population: Services Use and Characteristics. *Psychiatric Services*, 67(12):1334–1339, 2016.

Oakland-Berkeley-Alameda County CoC. Centering Racial Equity in Homeless System Design, December 2020. URL `https://everyonehome.org/wp-content/uploads/2021/02/2021-Centering-Racial-Equity-in-Homeless-System-Design-Full-Report-FINAL.pdf`.

Padmavathi Patlolla, Vandana Gunupudi, Armin R Mikler, and Roy T Jacob. Agent-Based Simulation Tools in Computational Epidemiology. In *International Workshop on Innovative Internet Community Systems*, pages 212–223. Springer, 2004.

Dereck W Paul Jr, Kelly R Knight, Pamela Olsen, John Weeks, Irene H Yen, and Margot B Kushel. Racial Discrimination in the Life Course of Older Adults Experiencing Homelessness: Results from the HOPE HOME Study. *Journal of Social Distress and Homelessness*, 29(2):184–193, 2020.

Jared Reynolds, Zhen Zeng, Jingshan Li, and Shu-Yin Chiang. Design and Analysis of a Health Care Clinic for Homeless People Using Simulations. *International Journal of Health Care Quality Assurance*, 2010.

Vincent W Slaugh, Mustafa Akan, Onur Kesten, and M Utku Ünver. The Pennsylvania Adoption Exchange Improves its Matching Process. *Interfaces*, 46(2):133–153, 2016.

Amulya Yadav, Hau Chan, Albert Xin Jiang, Haifeng Xu, Eric Rice, and Milind Tambe. Using Social Networks to Aid Homeless Shelters: Dynamic Influence Maximization Under Uncertainty. In *AAMAS*, volume 16, pages 740–748, 2016.

Cody Zeger. Evaluating Project Roomkey in Alameda County: Lessons from a Pandemic Response to Homelessness. Report for the Alameda County Office of Homeless Care and Coordination, May 2021.