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Adaptive transit scheduling to reduce rider vulnerability during heatwaves

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ABSTRACT

Extreme heat events induced by climate change present a growing risk to transit passenger comfort and health. To reduce exposure, agencies may consider changes to schedules that reduce headways on heavily trafficked bus routes serving vulnerable populations. This paper develops a schedule optimization model to minimize heat exposure and applies it to local bus services in Phoenix, Arizona, using agent-based simulation to inform travel demand and rider characteristics. Rerouting as little as 10% of a fleet is found to reduce network-wide exposure by as much as 35% when operating at maximum fleet capacity. Outcome improvements are notably characterized by diminishing returns, owing to skewed ridership and the inverse relationship between fleet size and passenger wait time. Access to spare vehicles can also ensure significant reductions in exposure, especially under the most extreme temperatures. Rerouting, therefore, presents a low-cost, adaptable resilience strategy to protect riders from extreme heat exposure.

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Heat; public transit; agent-based model; optimization; public health

1. Introduction

It is widely believed that the sustainable growth of cities relies on increasing public transit use (Dulal et al., 2011; Hodges, 2010). However, increasing frequency, duration, and severity of heat waves and other extreme weather events caused by climate change threaten both engineered infrastructure that supports public transit as well as passenger comfort and health. Phoenix, Arizona, with average maximum daytime temperatures of 111°F during summer months, and the fastest growing population in the United States, is particularly vulnerable to extreme heat (Chow et al., 2012; U.S. Census Bureau, 2020; National Oceanic and Atmospheric Administration 2020). As climate change advances, the frequency of extreme heat events in Phoenix is projected to increase from 2.0 to 24.4 annual events by the year 2070 (Grossman-Clarke et al., 2010). Importantly, lower-income communities that have less residential air conditioning, fewer cooling centers, and streetscapes lacking vegetation, are more susceptible to the impacts from extreme heat (Chow et al., 2012; Voelkel et al., 2018). Households residing in these areas are also more dependent on public transportation and may be disproportionately exposed to heat during travel (Taylor & Fink, 2003).

Existing studies show that seasonal changes in temperature and weather push would-be transit users to different modes of travel and may result in the delay or cancellation of non-essential trips (Liu et al., 2017). The drivers of these behavior changes are numerous and complex. For one, the discomfort of waiting for transit is exacerbated under inclement weather conditions (Guo et al., 2007; Singhal et al., 2014). Additionally, the journey to the bus, usually made by foot, can be physically taxing during high temperatures, especially for the elderly and persons with a disability or a chronic illness. These responses are furthermore shaped by the culture, climate (average weather) and built environment of an area (Böcker et al., 2013; Dijst et al., 2013; Liu et al., 2017).

Transit agencies are already equipped with a range of tools and actions to shield passengers during periods of unpleasant and potentially dangerous weather. These include investments in shading structures and tree cover in the surrounding areas of a bus stop (Lanza & Durand, 2021). Air conditioning on vehicles and in nearby retail can also be critical for reducing exposure. Physical infrastructure investments are not the only tool available to agencies, however.

Adjusting transit schedules to reduce waiting times can lower the duration of exposure without needing additional engineered infrastructure and can be

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implemented quickly. When opting to adapt transit schedules, agencies may avoid the expenses of large capital investments, help maintain ridership levels, as well as limit health risks. Understanding the potential benefits of reallocation as a means of adapting to extreme weather and how disruptive such schemes would be to current fleet assignments could help agencies make informed decisions for their customers. This study develops and implements a rerouting model for minimizing passenger heat exposure for the regional transportation agency in Phoenix, Arizona.

1.1. Heat, transit, and human health

Despite the extensive efforts to understand the effects of weather on travel behavior, the negative impact of heat on ridership has not been sufficiently integrated into existing transport planning processes (Liu et al., 2017). Moreover, these studies neglect the potential effects heat may have on riders who continue to use public transit (Dzyuban et al., 2021). There are likely many reasons individuals continue to travel during dangerous heat conditions including, but not limited to, modal captivity, weather indifference, and inelastic travel demand with respect to weather. Mode captives refers to people who have no other mobility options available to them and weather indifference refers to the subjective experience of adverse weather conditions and, in this context, one's willingness to endure certain temperatures for a sustained period (Jacques et al., 2013). Such willingness is likely informed by a traveler's opportunity cost from cancelling or postponing work travel, namely, their elasticity of demand (Liu et al., 2015).

Exposure to heat extremes accounts for more weather-related fatalities than nearly all other extreme weather events combined and is a leading cause of weather-related deaths in the U.S. most years (Berko et al., 2014; Hyland, 2016). Heat stroke and the aggravation of existing medical conditions from heat exposure are common causes of emergency room visits, hospitalizations, and early mortality (Kenney et al., 2014; Kovats & Hajat, 2008; Michelozzi et al., 2009). Globally, exposure to extreme heat was estimated to result in 480,000 excess deaths per year (Zhao et al., 2021).

Epidemiologic studies have identified demographic, economic, and community characteristics that are associated with increased mortality and morbidity during periods of extreme heat (Reid et al., 2009). Determinants of increased exposure and sensitivity to heat include: lower income, older age, higher population density, lower tree density, outdated construction, and lack of air conditioning (Aminipouri et al., 2016). Research has shown that these characteristics cluster spatially in urban areas where transit ridership is concentrated and where discriminatory redlining has resulted in historical underinvestment in infrastructure (Harlan et al., 2013; Hoffman et al., 2020; Reid et al., 2009).

The potential for prolonged exposure to extreme temperatures for transit riders is far greater than for drivers. In most cases, transit use requires riders to expose themselves to the environment in three phases: ingress, waiting, and egress. Ingress and egress exposure are a function of the mode used and distance traveled to access transit stops and final destinations. As more than 75% of all transit riders walk to transit, the location of the nearest stop relative to a person's origin is a critical factor in transit-related exposure (Hess, 2012). By contrast, waiting-based exposure depends on the frequency of individual transit lines, their reliability, their capacity, and the physical characteristics of a station (Fraser & Chester, 2017).

Early research around heat exposure and transit use combines simulated urban meteorology with transportation activity diaries to assess outdoor heat exposure during non-motorized travel, including access trips to transit stops. In such studies, researchers find that socially disadvantaged groups are disproportionately exposed to transport-heat (Karner et al., 2015). Additional research shows that transit stop location and transit schedules contributed to variable heat exposure across transit systems and that users from areas with low density, few high capacity roadways, and irregular street networks are more likely to experience prolonged exposure when travelling to and waiting at transit stops (Fraser & Chester, 2017).

1.2. Adjusting bus transit schedules during heat waves

Bus transit network design and scheduling is a complex process that balances service quality, coverage, and directness. In most cases, transportation agencies are not profit-driven but their resources and operations remain constrained by available budgets (Desaulniers & Hickman, 2007). The primary competing alternatives are transit systems that serve large areas with limited frequency and those that serve small areas with high frequency.. The public transit planning process is typically divided into five steps, (1) network design (route structure and stop placement), (2) route frequencies, (3) timetabling, (4) vehicle scheduling, and (5) crew scheduling and rostering (Guihaire & Hao 2008). This analysis focuses on step two, specifically increasing transit frequencies to reduce waiting times for passengers.

Vehicle arrivals per hour along a given route is the most important factor affecting overall wait time. Traditionally, average waiting times at any stop have been estimated as half the "headway', or the time between bus arrivals; on-board surveys, however, contradict this assumed uniform arrival distribution (Fraser & Chester, 2017). Along infrequent routes, passenger wait times are significantly less than half the headway indicating rider knowledge of existing transit schedules. Increasing frequencies along such routes without providing advanced notice to riders may not significantly reduce average waiting due to the passenger arrival behavior. Conversely, average wait times along frequent routes are typically greater than the times predicted by transit schedules. Thus, adding vehicles to routes with intermediate frequencies present the best opportunity to significantly reduce passenger waiting times.

Transit frequencies are usually developed from demand estimates and agency standards for vehicle occupancy and minimum frequency (Ceder, 2016). Such estimates are typically derived from travel demand models that draw from an area's economic activity and population to produce top-down projections of trip generation and mode choice. Yet these models are incapable of 'chaining' trips together nor do they attribute trips to specific households, limiting the ability for planners to fully measure the equity-impacts of bus scheduling. To address these and other shortcomings, agencies have, in recent years, begun implementing advanced activity-based models (ABM): bottom-up estimations of travel demand that are generated from household attributes and an individual's anticipated behavior in areas beyond their home and across different times of day (Hafezi et al., 2018).

There are well-established models for determining transit frequencies to optimize economic and efficiency outcomes (Hadas, 2013). Increased calls to consider equity in transit service, coupled with an ABM's provision of disaggregated sociodemographic data at fine spatial resolutions, however, warrant the addition of new optimization criteria in planning models, not least, ridership's exposure to extreme heat. This could either be accomplished by adding vehicles to service, as agencies already do for special events, or reallocating existing in-service vehicles from other routes. This paper develops an optimization framework that reallocates existing vehicles and dispatches spare fleet capacities based on the heat vulnerability of riders and explores that framework using a case study of Valley Metro, the transit agency serving Phoenix, AZ.

2. Methods and data

2.1. Optimization framework

To minimize negative outcomes from extreme heat, an agency should maximize service to the areas that are most likely to rely on transit and most likely to suffer from prolonged exposure to high temperatures. In other words, an agency should minimize the combination of heat exposure and heat sensitivity, what the model hereinafter refers to as vulnerability. Individual exposure is assumed to be negatively correlated with income and cars per household, as wealthier households will retain the option of driving or foregoing travel completely (He & Thøgersen, 2017). Regional vegetation abundance is also included as it offers cooling and shading for pedestrians (Lanza & Durand, 2021). Heat sensitivity, on the other hand, is modeled by passenger age, which studies have identified as the primary risk factor for heat stress during physical activity (McGinn et al., 2017). The final component of passenger vulnerability in this model is the duration of exposure. Because agencies independently determine the frequency of bus arrivals, the optimization model described herein solves for the bus frequencies that will minimize wait times. Simply stated, the model aims to reduce wait times by as much as possible, for as many people as possible while accounting for each passenger's sensitivity to heat and their dependency on travel. It uses a non-linear constrained optimization solver for the entire bus service area of Phoenix's transit agency. The model is specified as:

Equation 1: Objective Function

$$Min \sum_i \sum_{j \in C_i} W_i(f_i) D_j V_j$$

$$S.T.\ 1) \sum_i f_i < B\ \ 2) M \le f_i \le N, \in Z \quad i$$

$$Where: i = Transit\ route\ \&\ j = Microan\ alysis\ zone$$

$$W_i(f_i) = Average\ waiting\ time\ for\ route\ i \left(\frac{runtime}{vehicles}\right)$$

$$C_i = Microanalysis\ zones\ served\ by\ transit\ route\ i$$

$$D_j = Transit\ demand\ in\ microanalysis\ zone\ j(\#\ of\ TransitRiders)$$

$$V_j = Heat\ vulnerability\ of\ microanalysis\ zone\ j$$

$$f_i = Frequency\ of\ route\ i\left(\frac{vehicles}{runtime}\right)$$

$$B = The\ total\ number\ of\ buses\ currently\ operating$$

$$M = NIOSH\ Minimum\ allowable\ frequency\left(\frac{vehicles}{runtime}\right)$$

$$N = Maximum\ allowable\ frequency\left(\frac{vehicles}{runtime}\right)$$

The model assumes exposure to primarily be a function of wait time $W_i(f_i)$, demand D_j, and vulnerability V_j, subject to two main constraints. The first constraint, B, represents the total agency fleet size, which provides an upper bound on the total number of buses that can be assigned across all routes. While total fleet size is typically a constant, Valley Metro, like many agencies, has the capacity to dispatch spare vehicles to increase capacity. To observe the sensitivity of outcomes to the fleet size, B, the model is run for five different capacity multiples ranging from 0% to 20% increases in normal fleet capacity; the latter is the official spare fleet capacity reported in Valley Metro's 2020–2024 Short Range Transit Program and is also the maximum spare fleet size allowed by the Federal Transit Administration (Valley Metro – Regional Public Transportation Authority (RPTA), 2019).

The second constraint, N ensures that the number of vehicles servicing a route produces wait times that are below the National Institute of Occupational Safety and Health's (NIOSH) heat exposure duration standards and above an impractical lower limit of five minutes. NIOSH's standards were developed in 2016, with the Centers for Disease Control and Prevention, to inform employers about heat safety standards (Jacklitsch et al., 2016). These are based on the Wet Bulb Globe Temperature, a holistic measure of 'experienced' heat, the metabolic rate of an activity, and the availability of engineering controls to reduce heat stress (e.g. air conditioning, shade). In the absence of alleviating heat stress, the institute recommends 'administrative controls', or more simply stated, rest periods to allow for the body to cool. These guidelines are drafted separately for 'heavy', 'medium', and 'light' forms of work. The administrative control guidelines for 'light' work are used to parametrize maximum wait times in the above model for five different extreme temperature scenarios – 106°F, 107°F, 108°F, 109°F and 110°F. Finally, vehicle bunching, a reliability issue caused by excess vehicles, is known to occur on high frequency routes in high demand areas during peak periods (Camps & Romeu 2016). Adding vehicles to routes already experiencing bunching may exacerbate this problem. Accordingly, the minimum allowable headway in the model, or maximum allowable frequency, N, is set to correspond to five minutes.

To assess the optimization's sensitivity to the two imposed constraints, the model was run for each possible combination of fleet size and maximum frequency equaling 25 scenarios total. The optimization problem was solved in MATLAB using the 'fmincon' function which implements an interior point algorithm to find a globally optimal fleet allocation. The model produces a non-integer value for bus vehicle allocation and therefore can be interpreted as either a theoretical representation of service capacity or buses servicing only a segment of the route.

2.2. Transit schedule data

The geography, service frequencies, and current fleet allocations of individual routes are derived from the 2020 General Transit Feed Specification (GTFS) data for Phoenix's regional transit agency, Valley Metro (Valley Metro, 2020). The number of vehicles needed to produce a certain headway on a given route, f_i, is estimated by dividing the time it takes to complete a route, its runtime, by the route's average headway. Conversely, the wait time for a given route can be determined by dividing the runtime by the route's fleet allocation. For example, a route that on average takes half-an-hour to complete with buses arriving every 10 minutes, would require three buses. Given that headways and runtimes are not equal across all times of day nor all days of the week but rather fluctuate in response to demand across different stops at different times, estimates are based on the modal head of weekday service.

2.3. Transit demand

Transit demand, D_j, is determined using the output of the Maricopa Association of Governments (MAG) ABM in 2018 (Maricopa Association of Governments, 2018a). Activity-based travel demand models capture household-level and person-level travel choices including intra-household interactions between household members across a wide range of activity and travel dimensions (Parsons Brinckerhoff, Inc, Arizona State University, 2010). The ABM used in this simulation is informed, in large part, by a 2017 household travel survey conducted by MAG that includes GPS activity-travel data from 6,073 surveyed households, as well as data from the American Community Survey (Maricopa Association of Governments, 2018b). Importantly, transit trips in the ABM do not indicate the specific mode of travel (e.g. light-rail, bus); rather they are categorized between premium and conventional transit accessed by walking, kiss-and-ride, and park-and-ride. Premium transit traditionally includes express buses, bus rapid transit, light rail transit, and commuter rail whereas conventional transit typically refers to regularly scheduled local services. This model simulates heat exposure for all premium and conventional transit trips that can be routed using the local bus network.

The ABM output details the daily travel movements of a simulated population of 3.8 million agents and 18.4 million daily trips. Only a small fraction (~150,000) of the modeled daily trips in MAG's region occur by transit. In addition to the location of transit demand the model output also allows one to isolate the transit demand by time of day. The general movement of agents reflects a pattern of leaving residential areas during the morning peak period (6–9am) for employment locations and the opposite pattern during the afternoon/evening peak (3–7pm).

At its most resolved spatial scale, the ABM identifies the origin and destination microanalysis zones (MAZ) – the smallest transportation spatial unit used by the planning agency – for each transit trip. The open-source routing software Open Trip Planner (OTP) is used to translate origin-destination pairings – imputed to be the centroid of each respective MAZ – into a specific transit bus line. OTP is a graph-based multimodal routing system that operates on a unified graph including links representing road, pedestrian, and transit facilities and services (Hillsman & Barbeau 2011). Focusing on all MAZ with sizes below the 98th percentile, the trip-weighted median MAZ area is 0.09 km^2 (μ = 0.38 km^2), such that the 'true' origin point of a trip within any single MAZ does not differ much from the centroid. Variance in size across the 8662 unique MAZs that were routed by OTP, though larger, remains small in absolute terms with a weighted standard deviation of 0.9 km^2. As MAZs are population weighted, the MAZs with the largest area and greatest potential error, account for only a small share of passenger trips.

OTP routing assumes a maximum walking distance of one mile to reach a transit stop and accounts for all possible transfers. All routing requests were made at the nearest hour of departure based on weekday service for the agency in February of 2020. OTP routing produced transit routes for 99.5% of trips across 72 bus lines. Importantly, for the optimization model, non-local and non-bus transit lines are excluded as they tend to be low-frequency, pre-scheduled commuter services, with predictable wait times.

2.4. Passenger vulnerability

Area population heat vulnerability indices V_M were developed for each MAZ based on the ABM-reported characteristics of each transit rider who begins a trip from that MAZ as well as the area's vegetation abundance. The formulation of vulnerability was adapted from relevant literature to develop an individual-scale, transit-specific metric. Specifically, standardized scores for income, cars per household, and age were combined with equal weight, given their correlations with transit dependency and health risk (Taylor & Fink, 2003). The inclusion of transit dependency assumes that under extreme heat conditions there will be a decline in transit usage, specifically among passengers with alternative private travel options. Accordingly, this model prioritizes servicing areas with the greatest number of residents who lack such options. Finally, to estimate heat vulnerability from the physical environment, the normalized difference vegetation index (NDVI) was estimated for each MAZ by computing the median NDVI 30-meter pixel value from 2020 July and August LANDSAT 8 imagery in the one mile area surrounding the MAZ centroid. This area matches the maximum walking shed allowed by the routing algorithm for any single traveler. All social and physical variables mentioned were min-max normalized and added with equal weight to produce a vulnerability index. The product of the vulnerability index and the ridership demand for a given bus route can be interpreted as the weights that drive the prioritization of fleet allocation in the model.

Equation 2: Area population vulnerability index

$$V_j = \sum_{i \in A_i} N[Z(I_i) + Z(C_i) + Z(G_i)] + N(NDVI_j)$$

$$\text{Where}: i = \text{agentand}$$

$$A_i = \text{set of agents with trips originating in MAZ} j$$

$$Z(x) = \frac{x - \mu(x)}{\sigma(x)}$$

$$\text{where}\, \mu = \text{meanand}$$

$$\sigma = \text{standarddeviation}$$

$$N(x) = \frac{x - min(x)}{max(x) - min(x)}$$

I_i = Individual/s Household Income
Ci = Cars per household of individual
Gi = Age of individual

$NDVI_j$ = Normalize Difference Vegetation Index surrounding centroid of MAZj

Our approach marks a noteworthy advancement in precision compared to current vulnerability estimations by using ABM household and person characteristics. That is, while traditional ridership characteristics are imputed from aggregated census data for *residents* in a spatial unit, our vulnerability estimates are based on *traveler* characteristics and, in turn, capture a more accurate sample that includes non-home-originating trips.

3. Results

The ABM model counts 115,129 transit trips on an average weekday between the hours of 7 am and 6 pm, representing 0.79% of all trips completed during daytime hours, when the combination of sunlight and high air temperatures can be hazardous. According to the ABM, transit riders in Maricopa County are overall 11 years younger than the typical traveler, with a median age of 25, and hail from households with median incomes of $56,500, which is approximately 15% less than their non-transit counterparts. Cars per household for transit passengers is 1.77 compared with 2.14 for non-transit travelers.

Across all fleet capacity multiples, the mildest heat exposure of 106 F, benefitted the most from rerouting, realizing reductions in the demand-headway weighted vulnerability of over 20% for the standard bus fleet capacity and up to 40% when the maximum available fleet is used. Improvements stemming from capacity increases tend to be linear (Figure 1), suggesting that routes served by additional bus capacity contribute equally to the objective outcome. By contrast, when keeping capacity fixed, there is a nonlinear decline in improvement as the temperature increases, i.e. maximum allowable wait time decreases. Notably, at the extreme temperature of 110°F, there are not enough buses in the agency fleet to meet the wait-time constraint of 15 minutes for all bus lines. Rather, the minimum headway that can be realized for the entire local bus network using its standard fleet is 25 minutes. It is at

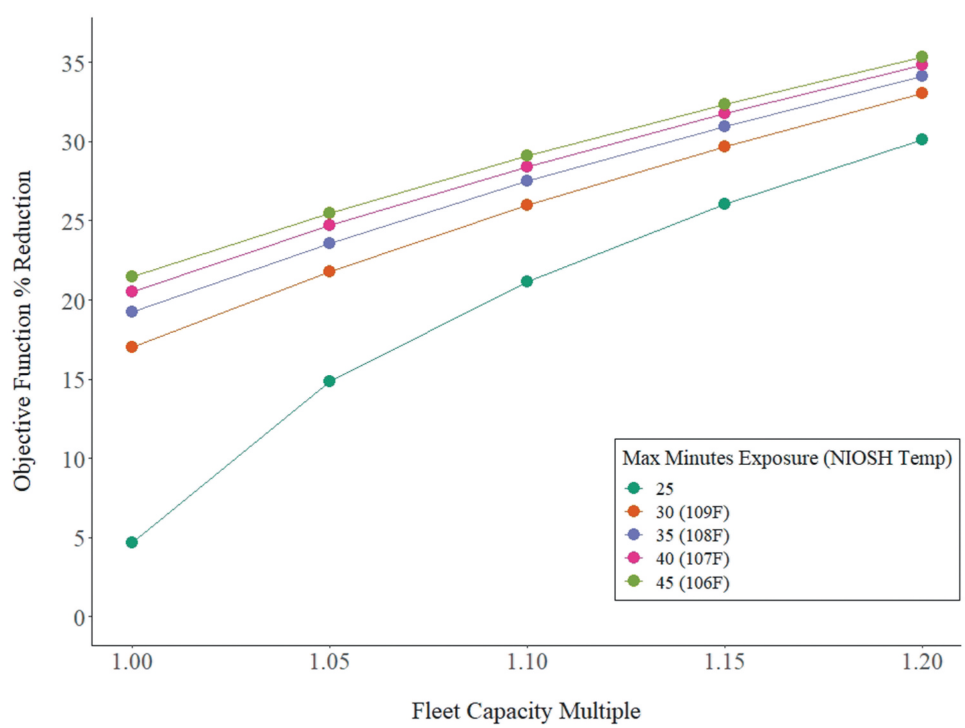

Figure 1. Optimization objective function improvements and fleet change magnitude. The Y-axis is the percent reduction of the optimized objective outcomes relative to the baseline schedule's unoptimized objective outcome. As the vertical spacing between points for a given capacity multiple illustrate, there is a nonlinear reduction in exposure as the maximum allowable wait time is reduced. As capacity increases, there is a linear reduction in risk – except for scenarios with most extreme heat, which exhibit nonlinear improvements in the objective outcome. The minimum achievable wait time (maximum exposure duration) for all routes was 25 minutes, for which there is no official corresponding NIOSH temperature.

this temperature scenario that capacity increases produce the greatest benefit by reducing headways for the most vulnerable routes; specifically, a 5% increase in fleet size corresponds to a 15% improvement in the objective outcome.

The observed results stem from both the uneven demand across the system and the inherent nonlinearity in headways which are inversely related to fleet size. Indeed, each incremental bus added to a route has a diminishing return on wait time equal to the inverse fleet size, squared. It follows then that a bus line with pre-existing small headways will see little gain from fleet additions. By contrast a line with large headways and moderate exposure, will see a large improvement from an increase in service. Simply stated, few lines carry most of the exposure and the model prioritizes those few lines with more buses to realize large reductions in riders' heat exposure. Any subsequent service improvements will have more moderate effects on outcomes. Spare fleet capacity makes the greatest difference under extreme temperature scenarios when the requirements of NIOSH compliance overwhelm the network.

NIOSH standards interact with the skewedness of passenger demand as well. This can be seen in Figure 2, which shows select few outliers in the objective function coefficients, i.e. the vulnerability index multiplied by the demand. When temperatures increase, the model's requirement for meeting maximum allowable exposure time on *all* lines results in the diversion of buses from lines with high vulnerability and high ridership to lines with lower vulnerability and ridership. Furthermore, given that allowable heat exposure has nonlinear stringency for each incremental degree, there is a corresponding nonlinear reduction in objective outcomes for increasingly severe temperatures when capacity is fixed.

Of practical importance is the number of buses that would need to be reallocated to achieve the optimal schedule. On average, across all scenarios, rerouting would require the reassignment of approximately 13.5% of the bus fleet (SD = 2.2%). Notably, 27 of the 72 lines see on average a 0.9 *decrease* in fleet size, based on the median outcome for each bus line across all scenarios. The remaining lines all show median increases in bus allocations compared to the existing agency schedule, with a maximum increase of 8.6 buses per hour for Line 19 which runs through Downtown Phoenix. Compared to our GTFS estimates of the agency's fleet sizes and assuming a bus capacity of 36 seats, the optimized model decreases the average load factor by 27% from 1.07 to 0.78. This is unsurprising given the model's emphasis on serving routes with large demand. Arterial lines, that traverse the downtown area as well as more densely populated neighborhoods to the east and west of the city center, are most served in the model's output (Figure 3). This reflects the higher population density west of Downtown Phoenix and coincident lower median family incomes. These lines also serve areas with younger residents who are less likely to own vehicles, including affiliates of Arizona State University.

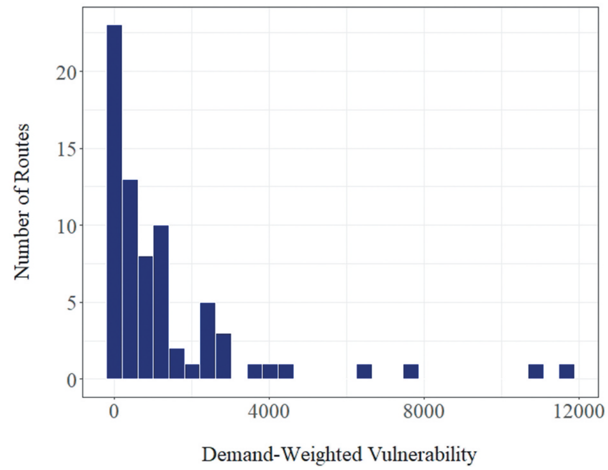

Figure 2. Distribution of MAZ demand-weighted vulnerabilities. The optimization model aims to minimize the wait time for the routes with the highest demand and vulnerability. The demand-vulnerabilities for all routes are represented as weights to the variable of interest – fleet allocation – when running the optimization model. The frequency distribution of these weights represents the distribution of vulnerable demand, or the total person-minutes scaled by the vulnerability indices for all origin MAZs boarding a given bus route. The positively skewed distribution demonstrates that a small number of routes carry a disproportionate number of vulnerable passengers.

4. Discussion

The model results highlight the context dependency of schedule optimization and rerouting to promote climate resilience in hot climates. Whereas under less extreme conditions, capacity increases confer proportional benefits to the objective, under more severe temperatures – when all routes must be equally serviced and baseline capacity is constrained – surplus vehicles offer significant benefits to reducing vulnerable exposure. Importantly, adding bus capacity to a line is limited by both a practical 'minimum' headway and the diminishing returns of additional buses. And finally, no amount of fleet reallocation would be able to satisfy NIOSH guidance on maximum allowable exposure for temperatures exceeding 110°F, without

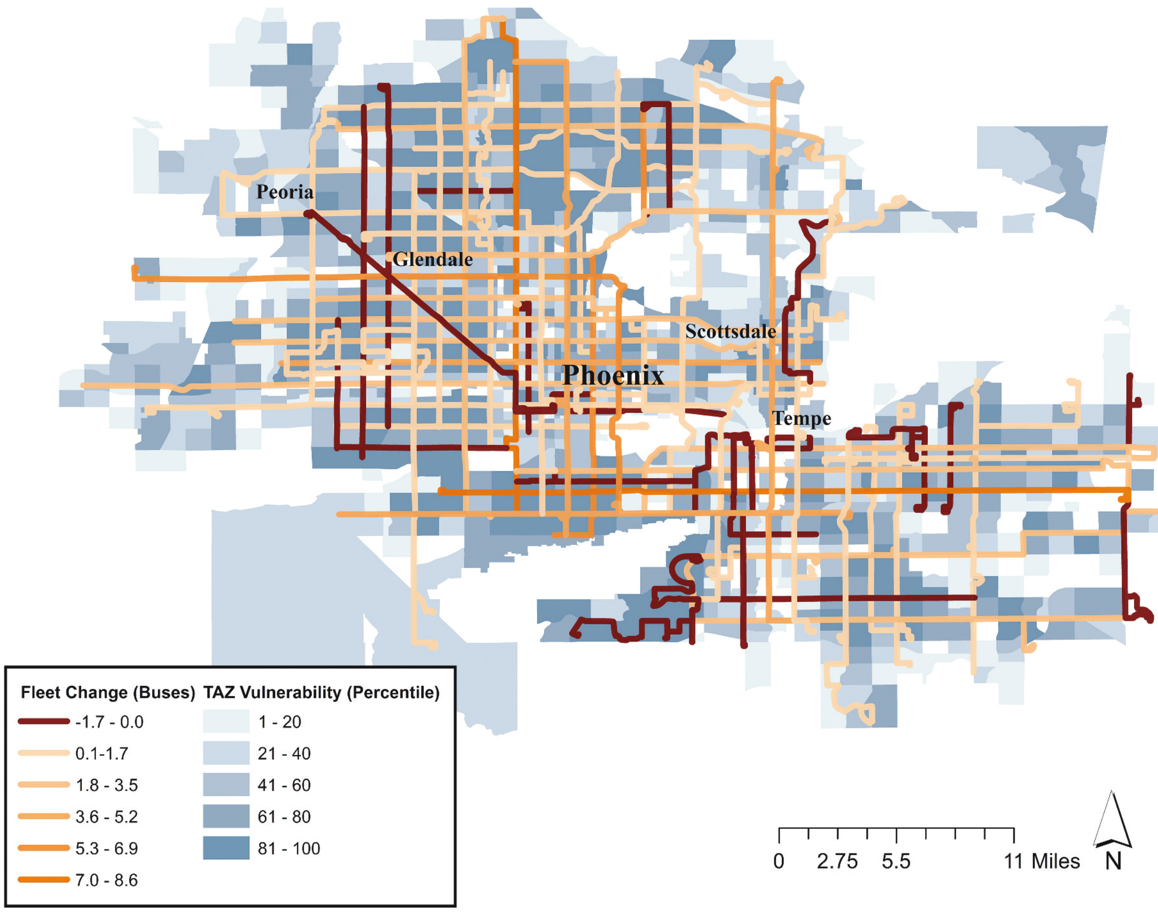

Figure 3. Map of Phoenix fleet reallocation. Background polygons correspond to transportation analysis zones (TAZ) – an MAZ's parent spatial unit. Each zone's vulnerability quintile is shaded in blue so that darker shades correspond to higher vulnerability. TAZ vulnerability is measured as the weighted average of all MAZ vulnerabilities subsumed by a TAZ and is used for visualization purposes only. Polylines correspond to the 72 local bus routes that were studied and are shaded according to the change in buses per runtime under the optimized scenario relative to baseline. Red colored lines experienced a reduction in service, with a maximum reduction of 1.7 buses per runtime. Orange shaded routes saw an increase in service with a maximum increase of 8.6 buses. For the few segments where routes overlap, the route with the highest frequency is shown.

a dramatic increase in fleet size. That is because the minimum number of buses per route needed to fulfill the maximum allowable wait time are so large, that the total number of required buses exceeds the total fleet size. Therefore, under the most extreme heat conditions, agencies would need to pursue alternative interventions that directly reduce heat exposure for a passenger and/or avoid the need to commute to and wait for a bus. These include, but are not limited to, cooled shade structures, improved tree canopy, first-last-mile micromobility connections, and on-demand transit services.

It is important to note that as a demonstration, the model presented in this paper makes simplifying assumptions that would need to be addressed prior to any real implementation. For one, rerouting and the dispatching of additional vehicles could increase agencies' operating expenses beyond allocated budgets. Further, many agencies have designated vehicles serving routes that are determined based on travel distance, terrain, and powertrain; by contrast, our model assumes that all vehicles can serve all routes. It may also be simplistic to assume that drivers would be amenable to sudden adjustments in route assignments and schedules. From the passenger standpoint, it is also worth noting that any changes to schedules would need to be communicated effectively, especially for the select routes that would experience a reduction in service.

The simulated scenarios also bear simplifying assumptions. For one, they assume uniform temperature throughout the study area, when the local built environment is known to cause variability in microclimates that impact human thermal comfort and health (Park et al., 2017). Yet, even with complete temperature information an agency would unlikely be able to adapt service to account for such high spatial variability in temperatures. . Additionally, NIOSH's 'light work' exposure thresholds while informative, are not directly based on travel activity. For this reason, the exposure thresholds introduced in the model should be interpreted as rudimentary benchmarks.

Finally, there are several improvements that could be made to the model, pending data availability. The first would be to obtain empirical wait times for different routes and stops to accurately quantify exposure. Having additional information on the bus stop infrastructure and egress exposure would also enhance such measurements. Additionally, the estimates of fleet assignments in the model are based on expected wait times and runtimes derived from GTFS and as a result overlook day-to-day and hour-by-hour fluctuations in schedules. Lastly, cost simulations associated with each fleet reallocation could further demonstrate the feasibility of any adaptive scheduling in applied settings.

These challenges notwithstanding, the model presents an advancement in its use of an ABM model that offers unmatched precision in traveler behavior and characteristics. These data inform changes to service operation that might offer significant cost savings over traditional hard infrastructure. They can be implemented relatively quickly and they can be easily adapted to unanticipated changes in infrastructure, demand, and weather. Future areas of research that could advance these models include enabling the partitioning of routes, whereby certain segments would be served at a higher or lower frequency, as well as logistic considerations that include bus depot location and bus driver availability. It would also be worth replicating this analysis for an agency like Los Angeles Metro, which has a larger bus fleet and covers an area with more temperature variability across space and time.

4.1. Implications

Cities throughout the United States have tasked public transit systems with securing myriad social benefits that include alleviating automobile congestions, reducing carbon emissions, and providing mobility to lower-income residents. To realize these goals, cities have invested heavily in the expansion of transit services and improving reliability. By comparison, the first-last-mile comfort of passengers prior to boarding and after alighting, especially as it relates to weather, has been overlooked. With climate change expected to increase temperatures in Phoenix and the nation, extreme heat has the potential to reverse hard earned improvements in service and safety.

This paper presents one method for protecting passenger comfort and health, leveraging the flexibility of bus systems to better serve routes with more vulnerable riders. It highlights the complex interaction between allowable heat exposure and the effect of bus capacity on wait-times – both of which follow nonlinear trends. The findings show that during milder summer heat (<110°F), agencies can achieve significant improvements with modest route adjustments and that during more severe heat events, the deployment of spare vehicles can secure large gains in passenger welfare. This is particularly true for agencies with skewed ridership, where a few lines carry most passengers. Given these findings, agencies might consider investments in building an adaptable workforce – training drivers for multiple routes and negotiating more flexible working arrangements – as well as ensuring the availability of spare vehicles before any extreme heat event. In doing so, agencies will help protect the health and comfort of their customers as well as equitably enhance the resilience of their systems.

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Data availability

The data that support the findings of this study were provided by the Maricopa Association of Governments. Restrictions apply to the availability of these data. Data inquiries may be sent to: mag@azmag.gov.

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