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Optimal Pedestrian Evacuation using Model Predictive Control*

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***Abstract*— During an emergency in a building complex, an effective evacuation is essential to avoid crowd disasters. This article presents a route guiding that minimize the evacuation time during the evacuating of pedestrians from a building.**

A dynamic network model, namely the point queue model, is used to form a linear programming problem whose solution is used as an evacuation plan. By continuously solving the problem using the new state as initial data a feedback control law is derived using Model Predictive Control.

The control law is tested on a microscopic pedestrian simulation for a building with five rooms and one respectively two exits. The simulation shows that the control law provides efficient and seemingly optimal, while taking the predicted future distribution of pedestrians along different routes into account. The control law further manages to handle minor errors in the provided layout information.

I. INTRODUCTION

During an emergency in a building complex, an effective evacuation is critical to avoid crowd disasters. It is therefore problematic that humans in emergency situations tend to behave in a way that prolongs the evacuation, for example by following the crowd and thus not using all exits efficiently. The wish to escape and the consequent emerging panic further makes them move faster than normal and push when they are slowed down by the surrounding crowd. Clogging might occur at doors and other narrow passages where: first, fewer people can pass than under normal conditions; and second, dangerously high pressure from the surrounding crowd might crush people, especially if they fall, causing what is sometimes referred to as stampede [1], [2].

Pedestrian models are a powerful tool that can provide insights into evacuation dynamics and that are used to evaluate the safety of different buildings during an evacuation. Microscopic pedestrian models have been able to reproduce many observed pedestrian phenomena, for example lane formation [2], clogging and faster-is-slower effects at bottlenecks [2] and crowd turbulence at extreme densities [3]. Further, they have successfully been calibrated to both empirically measured fundamental diagrams (flow-density relations) and to individual pedestrian trajectories [4].

Pedestrian models describe how pedestrians move towards a specified target, where the target usually is generated by a route choice model and given as an input to the model. Since different routes differ in length, safety and since congestion greatly increase the evacuation time, pedestrians escape route choice greatly influences the evacuation time. To correctly predict the route choice is therefore of great importance. The route choice has, for example, been modeled by assuming that pedestrians seek a local or global shortest or quickest path [5]; and by using game theory [6].

To decrease the evacuation time and the risk of congestion and panic, one could try to control the evacuation process by guiding the pedestrians towards safe and fast routes. This could for example be obtained by using emergency personnel and exit signs.

This paper proposes a method for obtaining an optimal evacuation route guiding for pedestrians from buildings. During most real life emergency evacuations, the ability to dynamically control the route choice of pedestrians is limited. Different buildings are also likely to have different needs for a such a control. Still, the optimal routes provided by the proposed method can give insights into how pedestrian should move in order to obtain more efficient evacuations. It will also enable the calculation of an upper bound on the possible efficiency increase that could be obtained by a good use of different control measures. The methods core is a set of linear equations that approximates the remaining evacuation time given a specific route guide and a corresponding approximation of the future evolution of the system. Although these equations cannot predict the evacuation time of an pedestrian model, they could still be able to provide a close to optimal evacuation when as a predictive in model predictive control (MPC).

The developed optimal control law is described in section II, together with the scenarios and the pedestrian model on which the optimal control law is evaluated. For comparison, the first scenario is simulated under the assumption that all pedestrians always choose the closest door. Section III will provide the results and conclusions are given in section IV.

II. MODELING AND CONTROL

A. Model Predictive Control

In MPC, the current state of a plant, in this case the pedestrian simulation, is used as input in a *predictive model* that gives a simplified prediction of the future states of the plant. The evolution of the plant is predicted until the, typically finite, time horizon T_h and an optimization algorithm is used to determine an optimal open-loop control law for the predictive model until the time $T_c \leq T_h$. Since all pedestrians eventually will leave the building during an evacuation, it is possible to find a finite $T_h = T_c = T$

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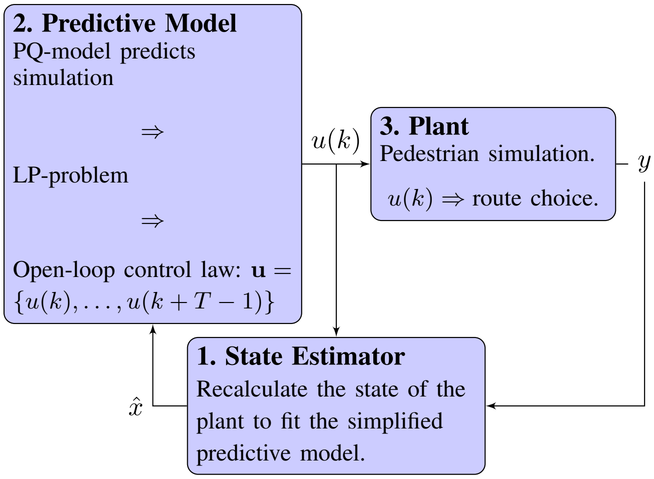


Fig. 1. Basic control loop in Model Predictive Control and what respectively part represents here. The predictive model is used to calculate an optimal open-loop control law. The control law is used for a specified length of time after which a new state is estimated from the plant and used once again by the predictive model.

that covers the entire evacuation time as predicted by the predictive model.

The open-loop control is used as input for the simulation and determines the route choice of the pedestrians. Since the predictive model does not exactly predicts the dynamics of the plant, the evolution of the plant will not follow the predicted optimal trajectory. After a specified time length, the new state is measured and used in the predictive model to generate a new open loop control law for the remaining evacuation time. This procedure is repeated until the evacuation is completed. The basic MPC control loop, and what respectively part represents here, is depicted in Fig. 1. For more theoretic background and stability conditions, the reader is referred to, for example [7], [8].

B. Point-Queue Model

Using the PQ-model, the pedestrian dynamics is simplified to flow on a (dynamic) network. The evacuation time for different evacuation strategies can thus be estimated by a set of linear equations. These equations will be used to form a LP-problem whose solution gives an evacuation plan that minimize the evacuation time. The derivation of these equations in this article are based on [9].

In the PQ-model, pedestrians are assumed to either move at the free-flow speed or queue with zero velocity. To exemplify how the model work, consider a room filled with pedestrians and a single door. To leave the room, pedestrians will first have to move to the door. In the point queue model, the time this takes is assumed to be independent of the density, so if the length to the link is L and the free-flow speed v_{ffv}, then the time it takes to reach the door is $\alpha = L/v_{ffv}$. Second, once the pedestrians reach the door there might be a queue and they cannot leave before everyone that arrived at the queue before them has left. If the flow (per meter per second) is given by the specific flow J_0, the flow (per second) through a door with width w is given by the bottleneck capacity $M = J_0 w$. In reality as well as in most pedestrian models, the flow actually decreases with density once the specific flow has been reached, so for high densities the PQ-model will overestimate the flow.

This way of estimating the evacuation time for different routes i also used in [6], where it is used to calculate the utility in a Nash equilibrium game, although only in a single room. How this can be used to model the flow of pedestrians in a network and to formulate a LP will be described below.

1) Governing Equations: The network is defined by $G(A, N)$ where N is the set of nodes and two nodes n, $m \in N$ is connected by a directed link $l = (n, m) \in A$, where n is called the *tail node* and m is called the *head node*.

Three equations determine how the flow evolves in this network. First, *conservation of flow on a link* gives a relation between the flow on a link and the inflow to and outflow from the link.With $x_l(k)$ as the flow at link l at the beginning of time step k; and $u_l(k)$ and $v_l(k)$ as the inflow to respectively outflow from link l during time step k, this gives:

$$x_l(k+1) - x_l(k) = u_l(k) - v_l(k). \tag{1}$$

Second, the flow into a node must equal the flow out from a node. Define $I_n = \{l \in A \text{ s.t } n \text{ is head node of } l\}$ and $O_n = \{l \in A \text{ s.t } n \text{ is head node of } l\}$. Further, define $u_n^s(k)$ and $v_n^s(k)$ as inflow and outflow to the network if n is a source respectively sink node. Then *conservation of flow on a node* gives:

$$\sum_{l \in I_n} v_l(k) - v_n^s(k) = \sum_{l \in O_n} u_l(k) - u_n^s(k). \tag{2}$$

To, third, model the *dynamics on the link*, three more concepts must be introduced. The delay time α_l gives the number of time steps it takes for flow to traverse the link, so inflow $u_l(k)$ at the tail node reach the head node at time $k + \alpha_l$. The bottleneck capacity M_l gives the maximum outflow from a link per time step, so $v_l(k) \leq M_l$. If $u_l(k - \alpha_l) > M_l$, some flow reaching the tail node during time step k will not be able to leave the link during that time step. Instead, it is aggregated in a point-queue $\lambda_l(k)$. This gives the dynamics of the point queue and the outflow to:

$$\begin{aligned} \lambda_l(k+1) &= \lambda_l(k) + u_l(k - \alpha_l) - v_l(k) \\ v(x) &= \min(M_l, \lambda_l(k) + u_l(k - \alpha_l)). \end{aligned}$$

In order to enable the formulation of a LP, this will here be relaxed to:

$$\lambda_l(k+1) = \lambda_l(k) + u_l(k - \alpha_l) - v_l(k) \tag{3}$$

$$v_l(k) \leq M_l \tag{4}$$

where $\lambda_l(k) \geq 0$ guarantees $v_l(k) \leq \lambda_l(k) + u_l(k - \alpha_l)$.

2) Adaption for Pedestrians in Building: To adapt the PQ-model for pedestrians in a building, the links will be divided into three different sets.

The set of *new-room links*, A^{nr}, contains those links where the tail and head node represent different sides of the same door. In Fig. 2, $(n_1, n_4) \in A^{nr}$. The new-room link does not

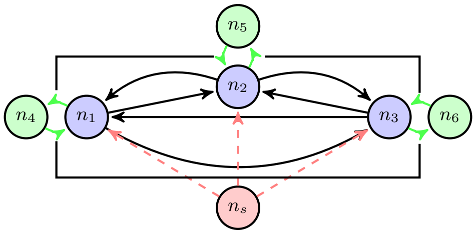


Fig. 2. Example of how a room is modeled as a network. The link (n_1, n_4) is a new-room link, (n_1, n_2) is a same room link, and $(n_s, n1)$ is a source link. To allow all pedestrians queueing in a same room link to be redirected towards another same room link, the bottleneck capacity of these links are infinite.

TABLE I

TRANSIT TIME AND BOTTLENECK CAPACITY RESPECTIVELY LINK TYPE.

	Transit time α_a	Bottleneck capacity M_a
A^{sr}	nint $\frac{l_a}{v_{ffv}\delta_{PQ}}$	∞
A^{nr}	0	$J_{s,\max} w_a \delta_{PQ}$
A^{s}	0	∞

represent any physical length and therefore the transit time $\alpha_l = 0$. The bottleneck capacity M_l of a new-room link is given by $M_l = J_s w \delta_{PQ}$, where J_s is the specific flow, w is the width of the door and δ_{PQ} is the size of a time step in the PQ-model. The set of *same-room links*, A^{sr}, contains those links where the head and tail node represent different doors in the same room. In Fig. 2, $(n_1, n_2) \in A^{sr}$. The transit time α_l for a same-rome link is $\alpha_l = \text{nint}\,\frac{l_l}{v_{ffv}\delta_{PQ}}$ where l_l is the length of the link, v_{ffv} is the free-flow velocity and nint is the nearest-integer function. There is no upper bound on the outflow from these links, i.e., $M_l = \infty$ in order not to constrain the ability to reroute pedestrians within the same room. Further, since the bottleneck capacity of a same-room link is at least as high as that of a consecutive new-room link, this bottleneck capacity do not influence the time delay from congestion in the network.

The set of *source links* contain those links where the tail node is a *source node*. In Fig. 2, the node n_s is a source node and thus (n_s, n_1) is an example of a source link. The source node is introduced to model the initial distribution of pedestrians in the network and every room where pedestrians are initially located have a source node. The source links models the initial route choice of pedestrians. For the same reason as for the same-room links, the bottleneck capacity for source links are infinite. To simplify initialization, the transit time α_l of source links are set to zero.

A summary of the above discussed properties for the different link types is given in Table I.

3) Cost function: The total time spent in the network is just the sum of the flow on each link at all time steps times the time step size, so the evacuation time is minimized if the total flow during all time steps is minimized. However, there are likely to be many control strategies that produce the same total evacuation time in the PQ-model. For example, some queueing pedestrians at different doors could, depending on the queue length, swap queues without influencing the evacuation time. To avoid the occurrence of such solutions a small cost c is induced on the inflow $u_l(k)$, giving the cost function:

$$V(x, u) = \sum_{l \in A} \sum_{k=1}^{T} \delta_{PQ}\big(x_l(k) + c \cdot u_l(k-1)\big). \qquad (5)$$

where the constant $c = 0.05$ were chosen small to not significantly influence the optimal route choice.

A higher value of c could be used to penalize complicated route choices. By including a cost for queues λ it would also be possible to penalize congestion.

4) Formulation of an Optimization Problem: The equations in (1)-(4) can be seen as constraints. With $V(x, u)$ from (5), the linear programming problem in (7) is given, where it should be observed that $u_n^s(k)$ is known on beforehand and introduced only to model the initial distribution of pedestrians. Further, $x_l(0)$ and $\lambda_l(0)$ gives the current flow in the network and $u_l(k)$ for $k < 0$ gives previous values of the inflow to the links.

C. Social Force Model

The social force model was chosen to simulate the movement of pedestrians. In the social force model, the collision avoiding behavior of pedestrians is modeled by social forces acting on every pedestrian from every other pedestrian and all walls. Combining these with a driving force and physical forces gives the acceleration for pedestrian i to:

$$m_i \frac{\mathrm{d}\mathbf{v}_i}{\mathrm{d}t} = \mathbf{f}_i(t) + \sum_{j\ (\neq i)} \mathbf{f}_{ij}(t) + \sum_{W} \mathbf{f}_{iW}(t) \qquad (6)$$

where m_i is the mass; $\mathbf{v}_i(t)$ is the velocity; $\mathbf{f}_i(t)$ is the driving force; $\mathbf{f}_{ij}(t)$ is the force on pedestrian i from pedestrian j; and $\mathbf{f}_{iW}(t)$ is the force from wall W. How these forces are modeled vary somewhat in literature. Here, the social force model with an anisotropy factor has been used, as described in for example [3]. The forces are then given by:

$$\mathbf{f}_i = m_i \frac{v_i^0 \mathbf{e}_i^0 - \mathbf{v}_i(t)}{\tau} \qquad (8)$$

$$\begin{aligned} \mathbf{f}_{ij} = & \Theta(\varphi_{ij}) A e^{\frac{r_{ij} - d_{ij}}{B}} \mathbf{n}_{ij} \\ & + k g(r_{ij} - d_{ij}) \mathbf{n}_{ij} \\ & + \kappa g(r_{ij} - d_{ij}) \Delta v_{ji}^t \mathbf{t}_i j \end{aligned} \qquad (9)$$

$$\begin{aligned} \mathbf{f}_{iW} = & A e^{\frac{r_i - d_{iW}}{B}} \mathbf{n}_{iW} \\ & + k g(r_i - d_{iW}) \mathbf{n}_{iW} \\ & - \kappa g(r_i - d_{iW})(\mathbf{v}_i \cdot \mathbf{t}_{iW}) \mathbf{t}_{iW}. \end{aligned} \qquad (10)$$

Here, $v_i = 1.5 + 0.26 p_i\,\mathrm{m/s}$ is the desired speed, where $p_i \sim \text{unif}(0, 1)$; $\mathbf{e}_i^0$ is the desired direction; $\mathbf{v}_i(t)$ is the current velocity; $\tau = 0.5\,\mathrm{s}$ the relaxation time; $\Theta(\varphi_{ij}) = \Big(\lambda + (1 - \lambda)\frac{1+\cos(\varphi_{ij})}{2}\Big)$ is the anisotropy function where φ_{ij} is defined by $\cos(\varphi_{ij}) = -\mathbf{e}_i^0 \cdot \mathbf{n}_{ij}$ and $\mathbf{n}_{ij}$ is the normalized vector from pedestrian j to i; $A = 29\,\mathrm{N}$ and $B = 1\,\mathrm{m}$ are constants

$$
\begin{aligned}
&\text{minimise} \quad \sum_{l \in A} \sum_{k=1}^{T} \delta_{PQ}\big(x_l(k) + c \cdot u_l(k-1)\big) \\
&\text{subject to:} \\
&x_l(k+1) - x_l(k) = u_l(k) - v_l(k) && \forall l \in A,\ k = 0, \ldots, T-1 \\
&\sum_{a \in I_n} v_a(i) - v_n^s(i) = \sum_{a \in O_n} u_a(i) - u_n^s(i) && \forall n \in N,\ k = 0, \ldots, T-1 \\
&\lambda_l(k+1) = \lambda_l(k) + u_l(i - \alpha_l) - v_l(k) && \forall l \in A,\ k = 0, \ldots, T-1 \\
&v_l(k) \leq M_l && \forall l \in A,\ k = 0, \ldots, T-1 \\
&u_l(k) \geq 0,\ v_l(k) \geq 0 && \forall l \in A,\ k = 0, \ldots, T-1 \\
&x_l(k) \geq 0,\ \lambda_l(k) \geq 0 && \forall l \in A,\ k = 1, \ldots, T \\
&v_n^s(k) \geq 0 && \forall n \in N^{\text{sink}},\ k = 0, \ldots, T-1 \\
&v_n^s(k) = 0 && \forall n \notin N^{\text{sink}},\ k = 0, \ldots, T-1
\end{aligned}
\tag{7}
$$

that here has been calibrated to fit a fundamental diagram; $r_{ij} = r_i + r_j$ is the sum of the radius for pedestrian i and j with $r_i = r_j = 0.25\,\mathrm{m}$; d_{ij} is the distance between the center of mass of the two pedestrians; $k = 1.2 \cdot 10^5\,\mathrm{N/m}$ and $\kappa = 2.4 \cdot 10^5\,\mathrm{kg/m\,s}$; $g(x) = \max(x, 0)$ indicates if two pedestrians or a pedestrian and a wall is in contact; $\Delta v_{ji}^t = (\mathbf{v}_j - \mathbf{v}_i)\mathbf{t}_{ij}$ is the difference in velocity between two pedestrians where $\mathbf{t}_{ij} = (-n_{ij}^2, n_{ij}^1)$; and the parameters in the wall force is defined in the same way.

D. Applying Control

How the open-loop optimal control law calculated by the PQ-model is applied to the simulation depends on if: 1) the system is being initialized; 2) pedestrians are entering new rooms and should be assigned new desired doors; and 3) pedestrians should be rerouted and given new desired doors in the same room.

1) Source control: The source control determines towards which doors pedestrians are initially moving in the simulation. If M_r pedestrians are initially located in room r and this is the first time step in the MPC loop, the flow into the source node n_r^{source} during time step $k = 0$ is $u^s_{n_r^{\text{source}}}(0) = M_r$. The initial flow $x_l(0)$ and queue $\lambda_l(0)$ is zero for all links. By (2), it follows that:

$$
\sum_{l \in O_{n_r^{\text{source}}}} u_l(0) = u_n^s(0)
$$

where $l \in O_{n_r^{\text{source}}}$ defines the source links in r. The doors in each room has been ordered in a trivial way. Let the i:th door in the order be represented by node n_i. The source link $l_i = (n_r^{\text{source}}, n_i)$ is thus connected to the door. The $u_{l_i}(0)$ pedestrians in room r closest to the center of the door that has not yet been given a desired direction is then routed towards that door.

2) New room control: When pedestrians enters new rooms in the simulation, they are assigned a new desired doors. The proportion

$$
u_l^{prob}(0) = \frac{u_l(k)}{\sum_{l_n \in O_n} u_{l_n}(k)},\ \forall l \in O_n \tag{11}
$$

$$
k = \min i \in \{0, 1, 2, 3\} \text{ s.t. } u_l(i) > 0 \tag{12}
$$

is used to determine the probability $u_l^{prob}(0)$ that a pedestrian entering the door represented by node n is routed towards respectively door. To obtain a route guide even if the inflow predicted for the current step was zero, (12) uses the first $k \leq 3$ for which the inflow is greater than zero. If no k satisfying (12) exists, $u_l^{prob}(0)$ is equally large for all l.

3) Same room control: If, due to changed circumstances or errors in the predictive model, pedestrians should be redirected within the same room, a same room control is used. The total number of pedestrians to redirect to link $l = (n_t, n_h)$ is given by the inflow $u_l(0)$ minus an estimation based on (11) of the flow entering link l from outside the room. Let $l_{nr} = (n, n_t)$ be a new room link. Then:

$$
u_l^{\text{same room}}(0) = u_l(0) - u_l^{prob}(0) u_{l_{nr}}(0)
$$

This gives the number of pedestrians in the room that are currently moving towards the door at n_t but should be rerouted towards n_h. The $u_l^{\text{same room}}(0)$ of these pedestrians closest to n_h are then given n_h as desired door.

E. Scenarios for Evaluation of Control

The control law is used on simulations of two different but similar building layouts. The layouts are given in Fig. 3. Both layouts contains four room and the main difference is that scenario 1 only has one exit whereas scenario 2 has two.

To evaluate how well the proposed control strategy is able to provide effective route guiding and handle deviances, three different route choice strategies are tested for scenario 1: In the first, referred to as the *closest door strategy*, pedestrians always choose the closest door in their current room. In

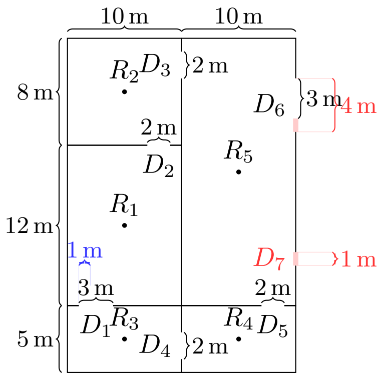
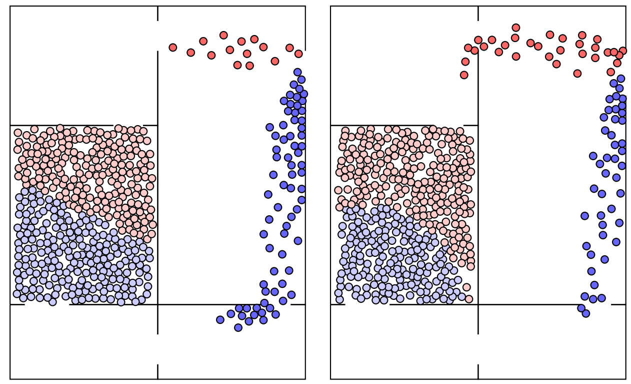


Fig. 3. Numbering and size of rooms and doors in scenario 1 (black) and scenario 2 (change marked with red). The difference between the two scenarios is that D_7 is added and that D_6 is widened for scenario 2. In both scenarios, 400 pedestrians are initially placed in R_1. In the PQ strategy with error, the optimal control law is calculated under the assumption that the width of D_1 is 1 m, marked with blue in the figure. In the pedestrian simulation, the door width is still 3 m.



(a) (b)

Fig. 4. In (a) the closest door strategy was used and in (b) the PQ-model was used to obtain route choices. The transparent pedestrians in R_1 shows how the pedestrians were initially choosing there routes and the non-transparent shows the evacuation at $t = 60\,\mathrm{s}$

the second, referred to as the *PQ strategy*, the proposed control strategy is used. The third, referred to as the *PQ strategy with error*, differs from the PQ strategy only in that the width of door D_1 is $w_{D_1}^{error} = 1\,\mathrm{m}$ when the optimal solution is calculated in the PQ-model, but $w_{D_1} = 3\,\mathrm{m}$ in the simulation. The number of pedestrians that should use the route including door D_1 will thus be underestimated.

III. Result

Fig. 4 - 5 shows the evacuation process for scenario 1. Blue pedestrians are initially moving towards D_1 and red towards D_2. From Fig. 4a it is clear that slightly to many pedestrians use D_1 in the closest door strategy. Using the PQ-strategy, as in Fig. 4b, the two groups are divided so that the last pedestrian in respectively group leaves the building at the same time. The outflow from door D_6 is therefore maximized when the PQ-strategy was used, as should be expected in an optimal evacuation. The possibility to redirect pedestrians is not used, indicating that the PQ-model is able to predict the dynamics with some precision. It is also clear that it would be better to use the PQ-model than to simply guide pedestrians to the closest door, although the difference is small.

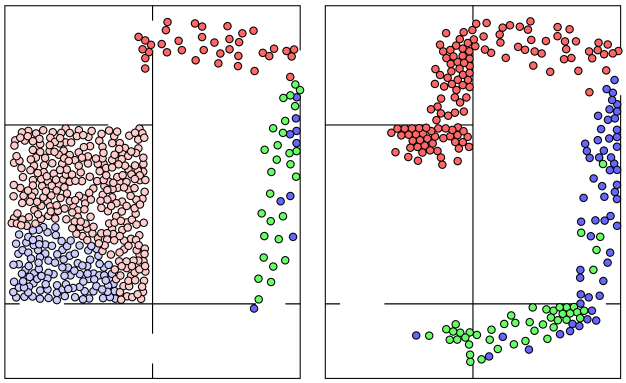
In Fig. 5, when the PQ strategy with error is used, the possible outflow from D_1 is underestimated and consequently less pedestrians are initially directed towards D_1. However, as people leave D_1, the optimal solution is updated and pedestrians are redirected (green group in figures) from the red group to the blue group. The last pedestrians that used D_1 respectively D_2 leaves the building at approximately the same time, again indicating an optimal evacuation. The final evacuation time for this strategy is almost identical to the PQ-strategy without error, as is the total number of pedestrians that use D_1 respectively D_2. This indicates that the control law is able to handle some errors in the predicted flow.

Fig. 6 shows the evacuation process for scenario 2 using the PQ strategy. Partly due to walking speed heterogeneity among the pedestrians, the initial flow through D_5 is within the capacity of the smaller but closer door D_7 and therefore all these pedestrians are directed towards D_7. When the flow through D_5 increases beyond the capacity of D_7, approximately half of the pedestrians are directed towards D_6. In that way, no clogging occur at neither D_7 nor D_6. At $t = 50\,\mathrm{s}$, right part of Fig. 6a, all pedestrians entering D_5 are routed towards D_7 where a small queue occurs. This is because the queuing time at D_7 is shorter than the walking time to D_6. Observe that if all pedestrians minimized their individual evacuation time, a queue would have formed at D_7 that took as long time to pass as the distance between D_7 and D_6 takes to walk. Also, if the heterogeneity in walking speed were taken into account, slower pedestrians should have been directed to D_7 in a greater extent than fast.

When using the PQ-model strategy on scenario 1, a static evacuation plan based on the initial solution would have been sufficient. However, in scenario 2 the route choice is dependent on the number of pedestrians still left in the system, and a static escape route would not have been able to use D_7 in an optimal way, and the prediction of the number of pedestrians that should use D_1 respectively D_2 would have been incorrect.

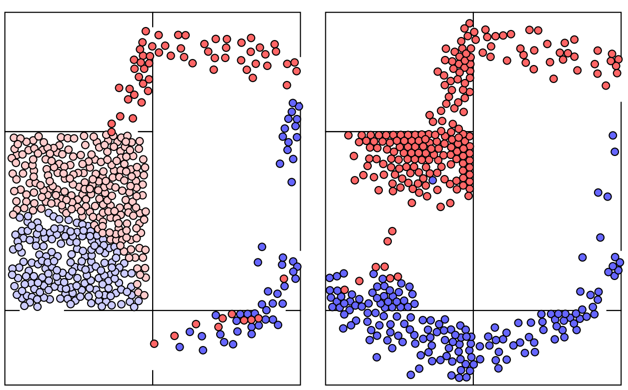
IV. Conclusions

The proposed method manages to find seemingly optimal evacuation strategies for the tested scenarios. The strategies obtained utilizes the maximum capacity of the exits for as long time and as fast as possible. This even though the predicted remaining evacuation time neither takes heterogeneity in walking speed among the pedestrians, nor the nonlinearity of the flow through bottlenecks into account. However, for the tested scenarios, the improvement in evacuation time obtained with the optimal route guiding compared to when pedestrians simply choose the closest door in the room is small. This is probably due to the small difference in total distance of the alternative routes.



(a) (b)

Fig. 5. Simulation result for PQ-strategy with error on scenario 1. Green pedestrians have been redirected from D_2 to D_1 since the flow through D_1 is higher than predicted. In (a), the transparent pedestrians in R_1 shows how the pedestrians were initially choosing there routes and the non-transparent shows the evacuation at $t = 60\,\mathrm{s}$. In (b), the evacuation at time $t = 40\,\mathrm{s}$ is given.



(a) $t = 0\,\mathrm{s}$ (b) $t = 20\,\mathrm{s}$

Fig. 6. Scenario 2. An extra exit is added. Initially, all pedestrians that enters R_5 through D_5 use D_7, and when the flow increases, more are directed towards D_6. When the last pedestrians use D_5, all are directed towards D_7. Pedestrians that enters R_5 through D_3 always use D_6. In (a), the transparent pedestrians in R_1 shows how the pedestrians were initially choosing there routes and the non-transparent shows the evacuation at $t = 40\,\mathrm{s}$. In (b), the evacuation at time $t = 20\,\mathrm{s}$ is given.

In future work, a more realistic escape route choice model for the pedestrians could be used together with control measures in accordance to the proposed method. With such a route choice model, it could also be possible to determine if some building layouts and some situations are more suitable for control of pedestrians.

In the current implementation, the parameters used in the PQ-model for the specific flow and free flow speed were the same as those used in the pedestrian simulation. Still, factors such as differences in flow through doors of different widths are likely to worsen the predictions of the model. By running simulations on the building layout of interest, these parameters could be estimated for each link.

The cost function in (5) is formulated to minimize the total evacuation time. Alternative cost functions could include more factors, for example penalizing queuing or including the safety on different routes. By adding a factor in front of x_a, dependent on the current safety of link a, the control strategy could be combined with a model describing, for example, the evolution of a fire.

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