Stationary and Time-Dependent Optimization of the Casino Floor Slot Machine Mix

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1. Introduction

We present a theoretical analysis of single and multi-objective non-linear optimization methods that address the casino floor optimization problem considering both linear and non-linear formulations of the problem.

- Modeling and optimizing the performance of a mix of slot machines on a gaming floor can be addressed at various levels of coarseness, and may have time-dependent trends.
- Aggregate data offers a limited opportunity to optimize the mix of machines. Fine-grained, time-dependent data for individual machines offers the most potential for detailed analysis and improvements to the casino floor performance.
- We address the impact of statistical noise and time-dependent trends on solutions, using both Gaussian and non-Gaussian distributions to model the performance of individual machines.
- We show that advanced methods from evolutionary computing can track trends in performance and continually adjust the optimal mix of machines. This would allow an operator to respond rapidly to customer preferences, and allowing a property to operate continuously near the optimal mix.

2. Modeling The Slot Floor

2.1 The Efficient Floor

This idealized model describes player behaviour on the casino floor. We begin with a simplified efficient floor where players:

- are thoroughly mixed throughout the slot floor
- can easily find their preferred machine type
- are indifferent to spatial region on the floor
- have no preference for crowded or isolated regions
- are indifferent to the placement of a machine on the bank

The probability that a player will choose machine *n* is given by:

$$p_n^{EF} := \frac{\psi_i}{N_i},$$

where ψ_i is a probability function specifying the likelihood that a player will choose a machine, and N_i is the number of machines of type *i*.

2.2 Non-Linear Effects

The "busyness" of the slot floor, Q, is described by: $Q := \frac{P_0}{N_0},$ where P_0 and N_0 are total number of players and machines. This busyness parameter follows a probability distribution p_q, measured at discretely binned values N_q, and normalized such that

$$\sum_{q=1}^{N_q} p_q = 1.$$

The duty cycle of a particular slot machine is the fraction of time that it is used, when the gaming floor is operating at busyness *Q* , defined by:

$$f_{n,q} := f_n(Q) = \min(1, p_n P_0(Q)).$$

The total coin-in for the floor is obtained by summing the coin-in over all machines and defined as

$$CI := \sum_{n=1}^{N_0} CI_n = \sum_{q=1}^{N_q} p_q \sum_{n=1}^{N_0} CI_i^0 f_{n,q},$$

where CI_i^0 is the measured baseline coin-in performance of a particular machine type *i*, which can be determined from the data. The win is defined as

$$WIN_{n,q} = w_i CI_{n,q},$$

where w_i is the "win fraction" representing the fraction of coin-in that the casino keeps for machine type.

4. Results - Tracking and Optimizing the Slot Floor Over Time

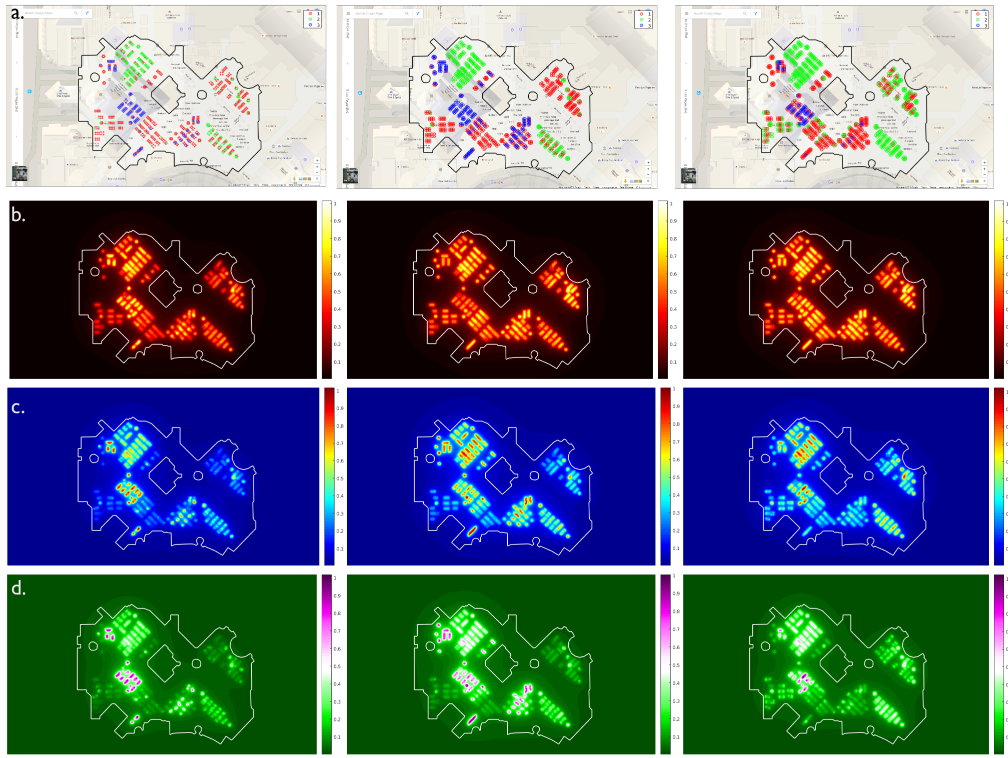

Fig. 1 (above) heat maps of optimal floors over three different busyness distributions *Q(t)* at different times. The maps show a. the floor layout, b. machine duty cycle, c. coin-in and d. win for each machine on the floor.

We model the floor using our multi-objective evolutionary optimizer called Ferret, which is embedded with artificial intelligence components. Based on fine grain artificial time dependent data, we model the slot floor and find optimized solutions to multiple objectives over time.

- The busyness of the floor changes slowly over time.
- The optimal slot floor layout changes over time in response..
- Fig. 1 shows heat maps of optimal floors over three different busyness distributions at different times. The maps show a. the floor layout; b. machine duty cycle; c. coin-in and d; win for each machine on the floor.
- Fig. 2 demonstrates the need for a non-linear model as coin-in saturates with busyness of the floor.
- Fig. 3 shows the trade off curves between coin-in and win objectives over different busyness distributions in time, *Q*. The optimization algorithm is multi-objective, meaning we can optimize, coin-in and win (for example) *simultaneously*, and map the trade off between the two.

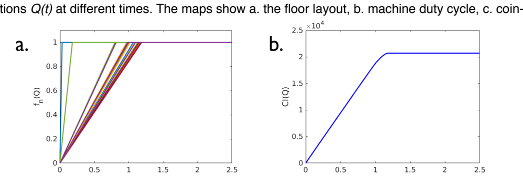

Fig. 2 Optimization results for efficient floor with 25 machines. Plots show a. the coin-in for each machine type and b. total coin-in for the floor. Saturation results because machines stop producing additional coin-in once $f_n(Q)$=1, at sufficiently high Q.

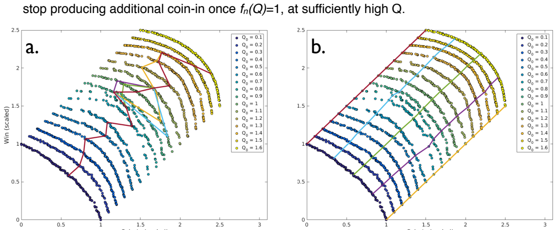

Fig. 3 Trade-off curves for various distributions of *p(Q,t)*. Each point represents an optimal floor model. a. shows tracking changes by making the smallest possible change to the number and type of machines and b. shows tracking changes with the same weight of coin-in and win.

3. Geospatial Modeling

3.1 Spatial Influences on Player Behaviour

The efficient floor probability function is modified by a spatial Δ_n:

$$p_n = \frac{p_n^{EF}(1+T(\Delta_n))}{\sum_{n=1}^{N0} p_n^{EF}(1+T(\Delta_n))}.$$

Here *T*(·) is a non-linear function that maps (-∞,∞) to [-1,∞).The Δ_n parameters represent spatial effects due to player preferences in regards to region (R); bank position (B); spatial preferences like proximity to walkways, restrooms etc. (S); and clustering preferences (C). Δ_n is defined as $\Delta_{n,q} = \Delta_n^R + \Delta_n^B + \Delta_n^S + \Delta_{n,q}^C,$

where the terms are defined as

$$\Delta_n^R = \delta_r^R \qquad \Delta_q^B = \delta_b^B$$

$$\Delta_n^S = \sum_{m=1}^{N_A} \delta_{i,j}^S d_{n,m}^{-\gamma^S} \qquad \Delta_{n,q}^C = \delta_i^C \sum_{m=1}^{N_0} f_{m,q} d_{n,m}^{-\gamma^C}.$$

Note that machine types *i* and *j* are determined from the machines identity. The distance between machines *n* and *m* is given by $d_{n,m}$.

3.1.1 Optimization Step 1: All the model parameters,

$$\mathbf{P} = (\underline{\psi}, \gamma^{\mathbf{c}}, \gamma^{\mathbf{s}}, \underline{\delta}^{\mathbf{r}}, \underline{\delta}^{\mathbf{B}}, \underline{\delta}^{\mathbf{S}}, \underline{\delta^{\mathbf{C}}})$$

are fit to machine level duty cycle and coin-in data. The model is fit minimizing the objective function

$$\chi^2 = \frac{(f_{n,q}^{model}(\mathbf{P}) - f_{n,q}^{data})^2}{\langle f_{n,q}^{data}\rangle^2} + \frac{(CI_{n,q}^{model}(\mathbf{P}) - CI_{n,q}^{data})^2}{\langle CI_{n,q}^{data}\rangle^2}.$$

3.1.2 Optimization Step 2: The model is optimized for maximum coin-in and win by varying the machine type at each site on the floor. The model predicts the behaviour of all the machines on the floor and we obtain optimal coin-in, win and duty cycle over the floor. This is done over varying probability distributions in order to track busyness Q.

3.2 Robustness to Noise

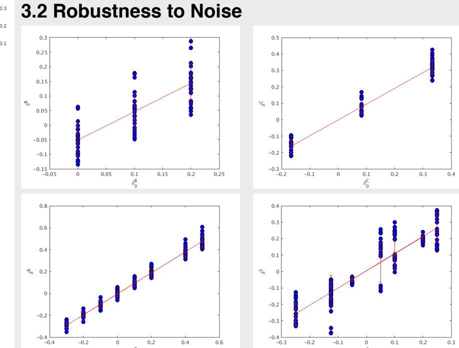

Fig. 4 Robustness to noise is shown by generating data from a known slot floor and adding 10% noise to duty cycle and coin-in. The red line shows the exact solution while the blue dots represent 25 inversions aiming to retrieve the solution. The scatter shows the accuracy to which the model parameters can be determined.

Bibliography

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