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LOOKING FOR BIG MONEY IN THE GREY ZONE. SIMULATION OF HIGH YIELD INVESTMENT PROGRAMS STRATEGIES

Abstract *High Yield Investment Programs (HYIPs) are online versions of a Ponzi scheme, a fraud that offers extremely high interest rates to attract investors – and pays them up to the moment when HYIP owner decides to run away with the money accumulated in the account. This article presents a simulation focused on the connections between investments in appealing websites, advertising, and run-away strategies to explore and describe one of the grey zone areas. The model is based to a large extent on real-life data acquired from HYIP monitors. In this paper, we have proven that advertising and layout have a great impact on an HYIP's balance. Moreover, most HYIPs are capable of gaining similar balance; however, there are also conservative strategies that significantly reduce profits.*

Keywords HYIP, Ponzi scheme, fraud, simulation, strategy

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1. Introduction

It is estimated that at least 6 million dollars is stolen each month by people running *High Yield Investment Programs* (*HYIPs*) [10]. HYIPs are online versions of a *Ponzi scheme* – they attract *investors* by offering them outstanding interest rates (from several up to hundreds of percentage points daily) coming allegedly from seizing great opportunities in the stock exchange, forex, metals, land trading, etc. Investors who join the program early enough have the opportunity to withdraw the money with promised high interest rates. The rest lose their money, since *HYIPs* **owners** run away with the accumulated funds at some point.

The goal of this paper is to test potential **strategies** used by HYIPs when they decide **to run away**. Furthermore, we have analyzed the influence of advertising (or lack thereof) and layout appeal on an HYIPs' balance. Finally, an attempt is made to assess whether investing in an HYIP's layout affects the choice of run-away strategies. Understanding this will help us to describe the HYIP phenomenon. We are not going to encourage anyone to invest in **scams**. On the contrary – we hope that the better they are examined, the greater the chance that at least some of the potential investors would save their money by not losing it in the **grey zone**.

The model is, to a large extent, based on real-life data acquired from *HYIP* **monitors** and **forums**. The details will be provided in the following chapters. It is important to underline that the simulation is necessary to better understand the behavior of HYIPs. Calculating this without assuming learning and mutation would only allow us to draw boundary results, such as maximum income. It would not show quantitatively how HYIPs are making decisions in the face of uncertainty. In the following chapter, related work will be discussed. In chapter no. 3, we describe the gathered data that we used to make the model as realistic as possible. Chapter no. 5 contains **the simulation model** specification (we also publish the simulator code as open-source software at `https://github.com/ResearchGeek/hyip-simulation`). The next one includes detailed results. At the end, we present conclusions and plans for future research.

2. Related Work

There are not many articles related strictly to HYIPs. Nowadays, probably the most robust is "The Postmodern Ponzi Scheme: Empirical Analysis of High-Yield Investment Programs" [10]. The authors have examined a 9 – month period of data from HYIP monitors (data aggregators containing information about HYIP solvency, interest rates, etc. – for more details, please see chapter no. 5) and show that there is no evidence of conspiracy between different aggregators. They also confirmed that longer HYIP lifetimes are associated with lower interest payments and longer mandatory investment terms. Finally, they have probably made the first estimation of monthly losses caused by HYIPs. The topic of HYIPs also appears in books and articles related to **digital currencies** [12] and **online security** [7].

From the broader perspective, HYIPs are usually considered when describing methods for detecting and fighting **cybercrime** [13]. Anderson, Barton, et al., in (probably) the first systematic study of cost of cybercrime, proposed the typology of crimes conducted via Internet: traditional crimes that are now "cyber" because they are conducted online (e.g., tax frauds), transitional crimes whose modi operandi have changed as a result of the move online (e.g., credit card fraud), new crimes that owe their existence to the internet, and finally, platform crimes (such as the provision of botnets that facilitates other crimes [9]. On the other hand, people who are unaware of an HYIP's nature can become less trustful when deceived, even in the area of completely-legal transactions on the Internet. This is one of the indirect costs of cybercrime [1].

HYIPs would be located somewhere between traditional crimes that are now "cyber" (because the idea comes directly from the old, well-known Ponzi scheme) and "transitional crimes whose modi operandi have changed as a result of the move online" (since the tools used to advertise HYIPs and payment systems were matched to exist in the online environment). On the other hand, people who are unaware of an HYIP's nature can become less trustful when deceived, even in the area of completely-legal transactions on the Internet.

As the problem of cybercrime grows, the research on how to increase financial safety on the web provides various possible enhancements and solutions. Morzy and Wierzbicki, in the article entitled "The Sound of Silence: Mining Implicit Feedbacks to Compute Reputation", present a method that avoids the unfavorable phenomenon of overestimating the reputation of online sellers by using implicit feedbacks [11]. Kaszuba et al. [8] describe a system that manages and learns from user feedback and considers an auction's context, possible types of complaints, and the structure of connections between those complaints in order to estimate the harmfulness of the reported complaints. Other approach is to use machine learning with regard to the problem of trust prediction in social networks [4] or to build more sophisticated trust management systems (that consider the consequences of misplaced or abused trust) [14]. Probably some of these solutions would also be applied to protect potential victims from investing in HYIPs, but a better understanding of the processes that rule HYIPs is required in order to build more comprehensive tools.

3. Dataset

We have grouped an HYIP's expenses into two separate groups. The first one (one-off expenses) is related to investments that an HYIP is required to make only once. The HYIP decides whether to spend $2500 on a more-attractive webpage layout in the beginning (counting on, in such a case, more investors deciding to deposit money) or opt for a less-expensive (and less-trustful-looking) layout (since research shows that nearly half of all consumers assess the credibility of sites based on the appeal of a website's visual design – including layout, typography, font size, and colour schemes) [6].

The second group includes all of the expenses that need to be done periodically to attract investors. As marketing activities, we understand each activity that helps HYIPs to become more popular among potential investors (advertising on forums and monitors, paid banners, etc.). We designed two types of advertising: basic ($50 per iteration) and professional ($150 per iteration).

The cost of all activities was roughly calculated on the basis of the offers that we managed to find on the web.

3.1. HYIP support – monitors

As was said, HYIPs enhance their credibility and attract investors in many ways. It is worth at least going through the most important elements to better understand the extent of this phenomenon and its way of functioning.

HYIP monitors are kind of data "aggregators" [10], collecting information about many HYIPs in one place. They focus on information about payments (whether an HYIP is still paying), but also usually provide some more robust data, such as an HYIP's lifetime, admin and user rating, payouts, minimum and maximum deposits, referral bonuses, etc.

3.2. HYIP support – webpage's layout

The layout is one of the essential elements in an investor's decision-making process whether to invest in a particular HYIP. This is based on two rationales: firstly, as mentioned earlier, people tend to be more trustful of visually-appealing websites; secondly, there is some financial explanation for this – if the owner puts more money to run the HYIP website, he or she needs more time to gain satisfying profits and run away. Considering a nice-looking HYIP that was just opened, we can assume that it will not be closed overnight but will last for a while. In our model, we have designed two types of HYIPs: one with a highly-appealing layout, and another with a much-less-appealing look.

3.3. HYIPs Investment Plans

Our analysis of HYIPs monitored by the AZHyip.com monitor (data gathered in March of 2014) shows that the vast majority of offers are one-day investments (3249 offers in the database). Only 93 offers required investing money for a week, and other periods of investment occasionally appeared. Naturally, HYIPs offer several types of investment plans, but one-day investments are clearly the most popular.

In view of these results, we decided to create a homogenous group of HYIPs with daily withdrawals. The same analysis has shown that, despite some unrealistic offers that appear on the web from time to time (like 100% of return on investment in one day), the majority of HYIP offers are in the range $0,1$–4% daily (63% of offers). The most-frequently-offered interest rate is in the 1–2% daily range.

Thus, we decided to assign a 2% daily interest rate to all HYIPs.

4. Problem definition

Since HYIPs have yet to be thoroughly examined, there are still many questions to which we do not know the answers. To take the first step in understanding how the advertising, appeal, and strategies are connected to each other, we have verified several hypotheses:

Hypothesis 1. *There are no differences in the proportion of strategies used by "appealing" and "non-appealing" HYIPs.*

Hypothesis 2. *The same strategies work similarly well for "appealing" and "non-appealing" HYIPs.*

Hypothesis 3. *HYIP's layout appeal does not affect the level of advertising used.*

Hypothesis 4. *Lack of advertisement influences an HYIP's balance.*

Hypothesis 5. *For similarly-effective strategies, HYIPs decide to run away at a similar point in time.*

5. Simulation

5.1. Why simulate?

We have chosen social simulation to examine our thesis, since "there are cases in which practical or ethical reasons make it impossible to realize direct observations: in these cases, the possibility of realizing 'in-machina' experiments may represent the only way to study, analyze, and evaluate models of those realities" [3]. HYIPs fulfil both of these conditions. Firstly, due to ethical restrictions, we could not run our own HYIPs and modify their strategies to check which one is the most profitable. Secondly, from a practical point of view, it was the only way to gather and analyze such types of data (since HYIPs are criminal activities, it is impossible to ask the owners to share the information about strategy and income with us).

Since simulation models are frequently used to predict certain events or tendencies ("if the goal is to predict interest rates in an economy three months into the future, simulation will be the best-available technique" [2]), their possibilities go much further [2]. In his "Simulation in the Social Sciences" article, Robert Axelrod points out seven different purposes of using simulation: "prediction, performance, training, entertainment, education, proof, discovery" [2]. Performance is related to artificial intelligence and mimicking human behavior in such cases as medical diagnosis, speech recognition, or function optimization. According to Axelrod, "to the extent that the artificial intelligence techniques mimic the way humans deal with these same tasks, the artificial intelligence method can be thought of as simulation of human perception, decision making, or social interaction" [2]. The "training" stands for all of the simulations that allow people to gain or excel in some new skills (e.g., flight simulators). "Entertainment" is close to "training" but does not require new skills, and such simulations can be fully devoted to fun. The next is "education". Simulation can also be proof that the thesis is correct, at least under the assumed conditions. Finally, simulation helps us "to discover important relationships and principles" [2].

HYIP simulation fits at least last two points: we are going to verify our hypotheses and at the same time we hope that we will discover relationships between such variables as strategies and balance account. Overall, there are many more reasons to analyze this problem with a simulation model. For example, we can try to explain the reasons standing behind the use of specific strategies by HYIP users. It needs to be highlighted that reasonable explanation does not mean the same as "predicting" which strategies would be used in a real-life situation by a particular HYIP owner. Since we do not have comprehensive real-life data and must simplify the model to be able to run it, the estimated balances should be treated very carefully, more as a point of reference rather than exact numbers. In any way, prediction is not always necessary in simulations [5].

5.2. Model description

To examine the phenomenon of HYIPs, we designed a multi-agent based computer simulation. Simulator coded in Repast Simphony 2.2 uses an evolutionary model with a Stochastic Universal Sampling (SUS) algorithm. The simulator runs with a static number of generations and iterations. Sanity tests confirmed that this number of iterations makes for reproducing an HYIP's financial model (acquiring money till foreclosure) as explained in the literature. Multiple-instance runs helps us to verify model tolerance of randomness of agent choice. A simulator tick represents a single day in the real world.

The creation of 960 HYIPs is the very first step. According to online HYIP monitors, this is the rough number of currently-running and paying HYIPs on the Internet. Their job is to produce investment offers and track ongoing investments occurring within them. All HYIPs in a single simulation share the following parameters (read once at the start of simulation): basic marketing cost, professional marketing cost, layout cost, basic marketing efficiency, professional marketing efficiency, and investor tendency to withdraw money. After being created, HYIPs participate in the evolution process, their state is reset after each generation ends (except the parameters for financial strategies that evolve).

After each generation of simulation, the HYIP's individual effectiveness (in terms of achieving the highest amount of accumulated money) is verified, and the best strategies for this goal are inherited by the next generation. In other words, **evolution players** are HYIPs, **fitness method** is the HYIP's account balance, and **players genes** are "exit strategies" described in paragraph no. 5.4.

The simulation scheme is presented on the Figure 1.

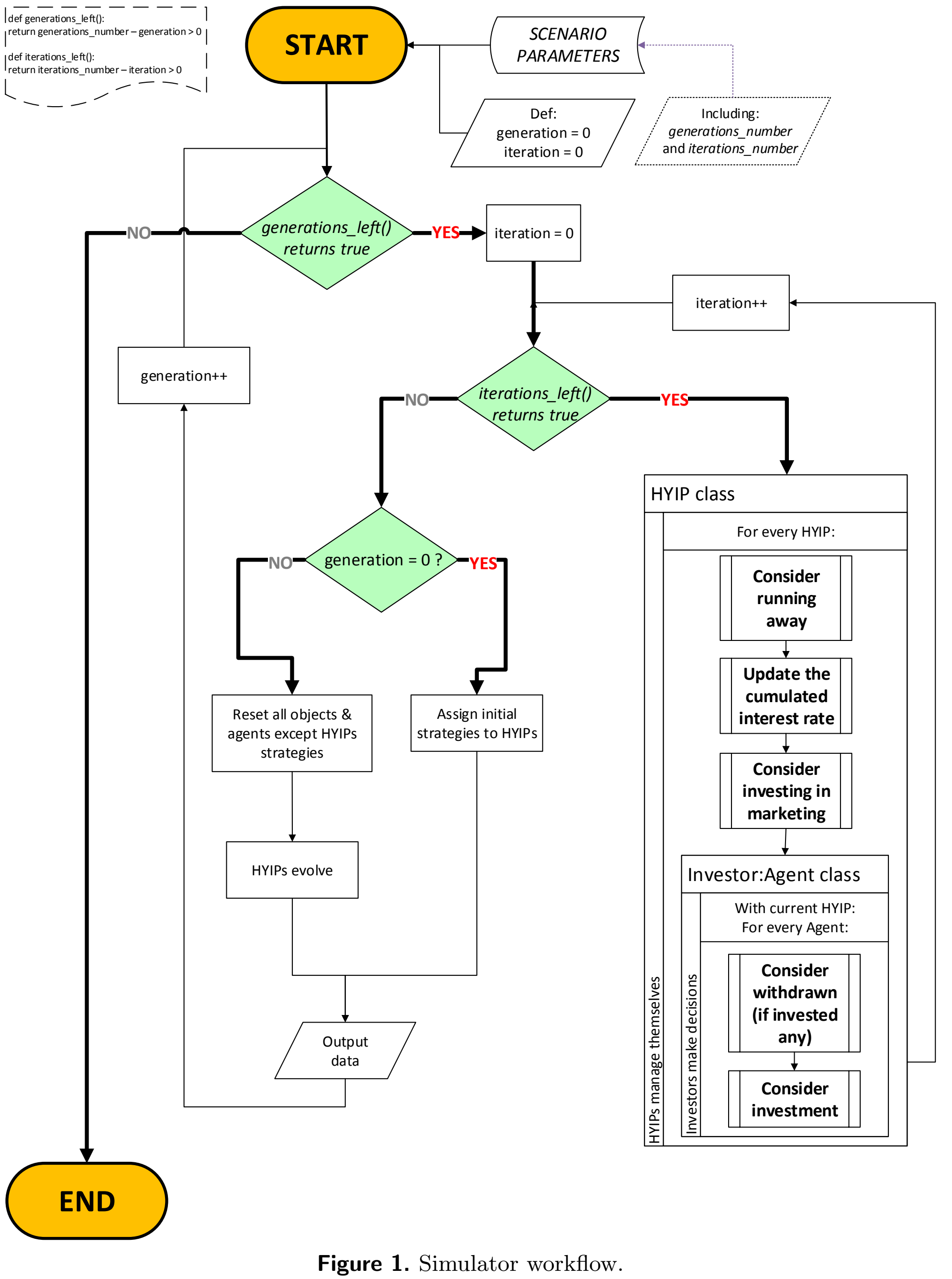

Figure 1. Simulator workflow.

5.3. Marketing, advertising and appearance

The cost of webpage design is chosen only once, yet it affects the probability of attracting investors. Paying for it is done at the beginning of the simulation and is a one-off payment. Half of the created HYIPs have been assigned "appealing" looks and the other half "non-appealing", which refers to layout quality. The ones with "appealing" look need to make a higher investment at the beginning, but their appeal to investors is higher.

There is no the real-life data that would be used to quantitatively determine the differences in appeal of HYIPs with good and bad layouts. We made an assumption that, depending on script quality, some probabilities of attraction can be assigned: on average, there is a 90% probability of attracting investors when a webpage is "appealing" and a 30% chance (on average) when it is "non-appealing".

Basic marketing cost and **professional marketing cost** are sums of expenses related to advertising an HYIP (reference bonuses, paid posters, adverts in social media, and so on). Basic marketing is, by definition, lower than professional marketing because it refers to more-basic advertisement. Professional marketing costs are higher, but they also affect investor decisions more (this efficiency is rejected by basic marketing efficiency and professional marketing efficiency parameters). The cost of both types of advertising is fixed at the beginning of the simulation.

Once the marketing for the HYIP in the current tick is chosen, it influences a gain to **cumulated marketing**. Cumulated marketing can be understood as efficiency in the current point of time, built from the history of previous expenses. Simulation scenarios have input parameters called **basic marketing efficiency** and **professional marketing efficiency**. Depending on the type of marketing chosen by an HYIP in the current tick, the cumulated marketing value equals to one or another. If the HYIP has "no marketing" strategy at the current tick, basic marketing efficiency is subtracted from the cumulated marketing. First and foremost, cumulated marketing is an attribute which is used in the advertisement computation formula, which is an s-curve function. To be sure that advertisement always stays within the range of $\langle 0; 1\rangle$, parameter m used in this formula is normalized to values from a range $\langle 6; 6\rangle$ as a proper fraction of cumulated marketing. It is assumed that HYIPs would not prosper when their accounts drop significantly below zero (such HYIPs are "running away"). Finally, there is the investor's tendency to withdraw money from an HYIP (estimated to be 10%). Next, we create agents in simulation who are investors interested in investing their money into various HYIPs through investment offers. They make investment decisions using their personal features, but with a shared algorithm utilizing these parameters.

In one HYIP, investors may invest between 1 to 10,000 units of virtual currency at one time (hereafter, we will call them "dollars").

5.4. Run away strategies

To decide when to run away with the money gathered on the account, HYIPs should have some fixed strategy that would approximate the optimal moment (i.e., close to the predicted maximum of possible profits). To meet this problem, we define a strategy as a discrete set of financial characteristics for a HYIP in a single point in time.

In our model, HYIPs can use one (or more) out of four available conditions with parameters to build an exit strategy. The criteria are checked together so the final algorithm works as a conjunction of one to four possible conditions, checked after each tick of simulation.

Once they are fit, HYIP "runs away" with the current amount of money, and neither pays nor offers more investments until the end of the simulation run. Each criterion also has a value to set. The four possible conditions are:

- **Money goal** (also called 'cash')
  Run away when current sum of money from investments exceeding the specified value. This condition represents a strategy to plan how much money an HYIP wants to gain from running away. The HYIP will wait to reach the target value; when the sum of investments exceeds it, this condition is fulfilled.
- **Income level** (called further 'income')
  Run away when income drops below the specified value. This condition represents a strategy to secure gains when HYIP income (gains from new investments minus payments for those who decide to withdraw) drops below a certain level.
- **Investment count**
  Run away when the number of active investments exceeds the specified value. This condition represents an intention to run away with as many investments as possible. An HYIP runs away only when the number of active investments is higher than the specified value.
- **Time**
  Run away after a specified number of days. This condition represents an HYIP's intention to run itself for a specified number of days.
  This guarantees some minimal time of HYIP presence.

Every combination of the above conditions is available. During the process of evolution, HYIPs evolve out of both sets of conditions and specific values for them. Added mutation ensures access to more combinations to find better strategies.

6. Results

Each results presented here are an average value for 10 simulation runs.

Firstly, we have designed a "model scenario", one that we believe reflects the real conditions the best. Afterwards, we manipulated some settings to check how it would affect the results. The "model scenario" assumed a 2% interest rate, mutation tendency 1%, professional marketing efficiency twice the basic (2% and 1%), investor tendency to invest: 10% and investor tendency to withdraw money: 10%.

6.1. Strategies

After first look at the data, we have decided to exclude HYIPs with no exit strategy. It was always a small group (around 0.2% of all HYIPs) that always went bankrupt, so it was not of much interest for our analysis.

The remaining fifteen strategies might be divided into two groups:

1. strategies used almost never (cash, cash and income, income)
2. strategies used with similar frequency (the remaining 12 strategies)

The Figure 2 shows the proportions at the end of simulation (in the last generation). It also includes splitting into "appealing" and "non-appealing" HYIP layouts.

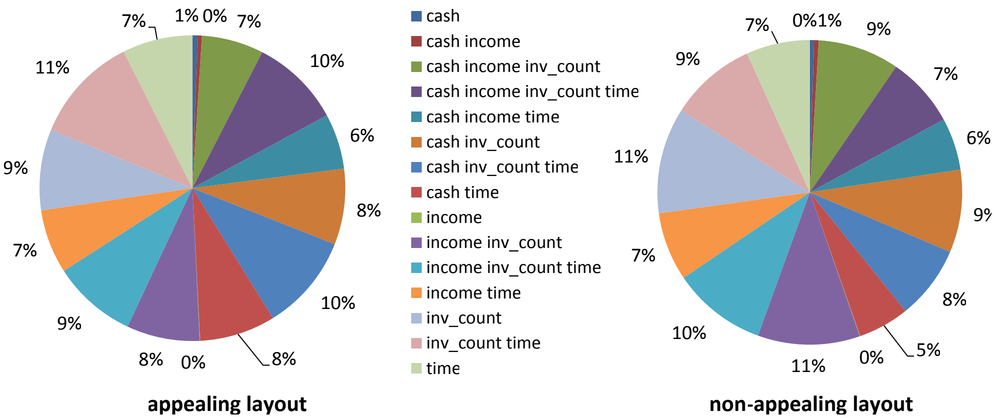

Figure 2. Strategies used in the last generation of simulation. Split by HYIP look.

This situation has an explanation in an HYIP's basic need – i.e., maximization of the amount of money on the account at the moment when the HYIP decides to run away with the money. Most strategies work similarly well and let HYIPs run away with nearly the maximum amount of possible income. "Cash" and "cash and income" work slightly worse. "Income" itself is the least-effective strategy, since it is the most conservative and makes HYIPs run away much too early to gain significant profits. The outcomes are shown in the Figure 3.

For the "12 remaining" strategies, we have calculated average and standard deviation (which is too small to be visible in the figure). Black lines represent HYIPs with appealing layouts, and grey ones – with non-appealing ones. As it turns out, the same strategies work for both types of HYIPs; but due to lesser investor attraction, "bad looking" HYIPs can gain less money overall.

Moreover, the results show that the "inheritance" of strategies is effective, and in a relatively-short number of generations, the average balance account stabilizes.

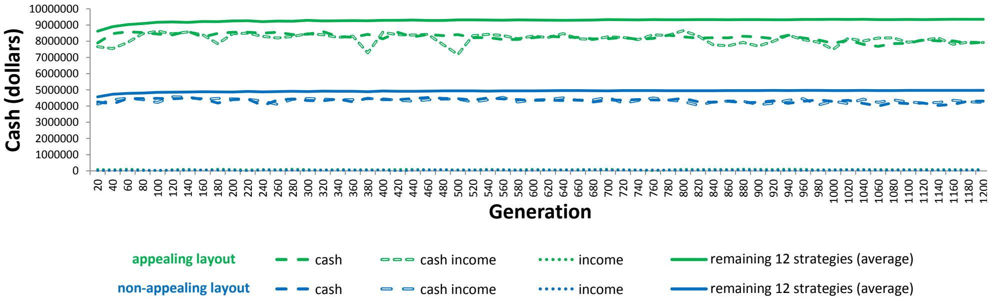

Figure 3. Average cash gained by HYIPs using listed strategies.

We have also simulated an HYIPs behavior under some different conditions. When we assumed that HYIPs would offer 3% daily return instead of 2%, the split of strategies used almost did not change. The only thing that changed was that the amount of cash gained by HYIPs – was lower since the withdrawals done during HYIP existence had to be higher.

More interesting findings come from manipulating investor tendency to withdraw money. As we said earlier, we assumed that this tendency would be 10% in "model scenario". Then, we increased this number to 50%.

With 50% investor tendency to withdraw money, both HYIPs with appealing and non-appealing layouts start to use strategies more frequently that include the number of investors who decided to participate in the HYIP (see Fig. 4).

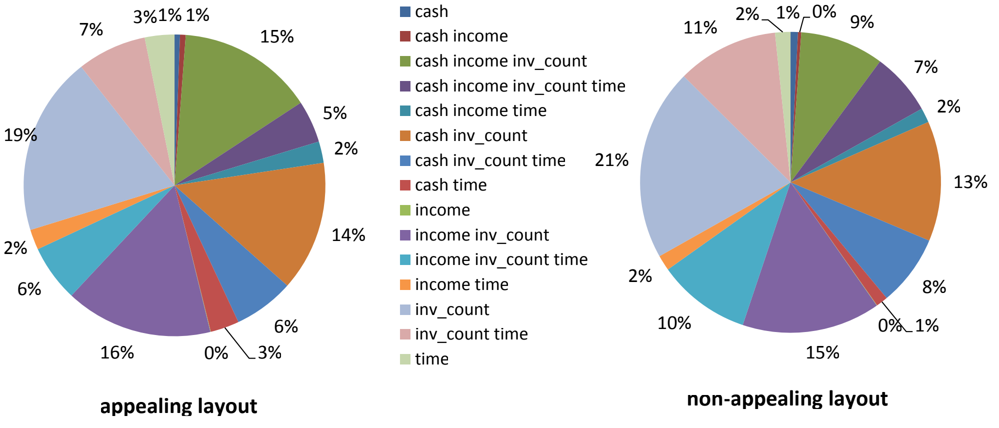

Figure 4. Strategies used in the last generation of simulation. Split by HYIP look. Investors tendency to withdraw money: 50%.

Surprisingly, this logical conclusion (avoiding too many investors who might withdraw money) is not more effective than the others. The proportion of cash gained by HYIPs using particular strategies remains the same as with the "model scenario", with linear offset caused by quicker cash outflow due to withdrawals occurring more often.

6.2. Marketing

Proper marketing is crucial in advertising and sustaining awareness of HYIP existence among potential investors. Instead of creating several different advertisement tools (such as monitors, banners, etc.), we decided to focus on the more basic problem: advertisement cost. Thus, we have created two types of marketing (basic and professional) and assigned to them the following costs: basic – 50 dollars, professional – 150 dollars per iteration (each generation consists of 200 iterations). The amount spent on marketing is cumulative, but if an HYIP decides at some point to resign from investing in any type of marketing, the coefficient of marketing efficiency drops; a similar situation would occur if an HYIP switches from professional to basic marketing. Marketing is one of the multipliers in the equation expressing the probability of attracting new investors.

As Figure 5 shows, all HYIPs learned very quickly to use primarily professional advertisement in order to avoid losing potential investors. We do not observe any differences between HYIPs with "appealing" and "non-appealing" layouts.

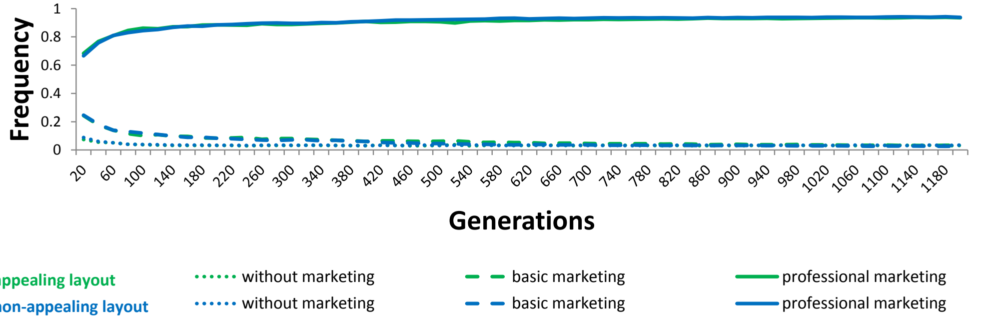

Figure 5. Probability of using each type of marketing, with split to appealing and non-appealing HYIPs.

We have also checked how HYIPs would behave if there would only be basic marketing available. It turns out that, in such a situation, HYIPs would invest in basic marketing in the same way as they invest in professional marketing.

Another thing that we examined was this: what would happen if marketing would not work at all? It is quite intuitive that spending on such useless activities would drop significantly (and simulation results confirm the probability of both types of marketing dropping below 5%). But the more-interesting fact is what happens to the amount of cash gathered in the account at the moment of running away – the average cash drops around 350 times.

6.3. Running away

At some point, each HYIP runs away with the money gathered in the account. This means that a website can still exist (or not), but withdrawals (and contact with the owner) are no longer possible. The news spreads all over monitors and forums, and in a few days, nobody wants to invest in such an HYIP.

According to simulation outcomes, HYIPs using most of the strategies would run at about the 50th day of existence on average (with the standard deviation varying from 0.4 to 2 days). This applies to both appealing and non-appealing HYIPs. "Cash" and "cash and income" strategies cause HYIPs to escape earlier, around the 40th day. The strategy that makes HYIPs run away the earliest, is "income", as it takes into account cash inflows and probable outflows (and as we said earlier, this is the most conservative strategy).

If we assume that an HYIP would offer 3% daily profits, then the average HYIP life span would be shorter – for the 12 best strategies; it would last around 45 days, for "cash", and "cash and income" – less than 40. For "income" only, it will still be 10 days; as around this day, the "income" strategy starts to predict an HYIP's downfall.

For HYIPs offering 2% daily profit but copying with 50% investor tendency to withdraw money, the lifetime would be even shorter and last respectively: for 12 best strategies – 40 days, for "cash" and "cash and income" – 33 days, for "income" only – 10 days.

The factor that shortens an HYIP's lifetime the most is the lack of advertisement. If marketing was not effective at all, HYIPs would exist from 15 to 25 days (except for "income" strategy – these HYIPs would still exist for only 10 days).

7. Conclusions and future research

In this paper, we have verified several hypotheses. We have shown that for the "model scenario", there are no differences in proportions of strategies used by "appealing" and "non-appealing" HYIPs. Differences in the proportions of strategies appear when investor tendency to withdraw money grows to 50% – but it does not affect proportions of an HYIP's balance.

We have also shown that, regardless of appeal, HYIPs use strategies in similar proportions. Even changing the daily return or the investor's tendency to withdraw money have no impact on these proportions. Moreover, we discussed advertisement impact on HYIP balance and found out that marketing activities are crucial when considering it. Yet, we did not find any differences in using advertisement between HYIPs with "appealing" and "non-appealing" layouts.

Finally, we demonstrated that HYIPs that use similarly-effective strategies decide to run away at a similar point of time.

The model described in this paper is an introduction to more-sophisticated consideration. In future research, we plan to diversify HYIPs, introducing them with weekly withdrawals. We will also work on the differentiation of investment rates and probability of withdrawals. Finally, we intend to introduce a market model where investors would have limited financial resources and HYIPs would not only need to be good enough to attract investors, but also be better than their competitors.

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