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Investigating technical trading strategy via an multi-objective evolutionary platform

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ABSTRACT

Conventional approach in evolutionary technical trading strategies adopted the raw excess returns as the sole performance measure, without considering the associated risk involved. However, every individual has a different degree of risk averseness and thus different preferences between risk and returns. Acknowledging that these two factors are inherently conflicting in nature, this paper considers the multi-objective evolutionary optimization of technical trading strategies, which involves the development of trading rules that are able to yield high returns at minimal risk. Popular technical indicators used commonly in real-world practices are used as the building blocks for the strategies, which allow the examination of their trading characteristics and behaviors on the multi-objective evolutionary platform. While the evolved Pareto front accurately depicts the inherent tradeoff between risk and returns, the experimental results suggest that the positive correlation between the returns from the training data and test data, which is generally assumed in the single-objective approach of this optimization problem, does not necessarily hold in all cases.

1. Introduction

The development of technical trading strategies (TTS) has always been an important financial subject, garnering vast amount of interest from researchers for many years. Essentially, TTS are trading rules based on technical analysis – forecasting of future market movements based on the past history of market actions. However, this methodology directly contradicts the Efficient Market Hypothesis (Fama, 1970), which states that future market prices are completely random and thus unpredictable since all the information available is already being reflected in the current market prices. In more technical terms, the stochastic movement of markets prices is purely Markovian (Korczak & Roger 2002). As such, economists have always been highly skeptical over TTS in general (Neely, Weller, & Dittmar, 1997).

Nevertheless, TTS are still widely used by professional traders (Fyfe, Marney, & Tarbert, 1999). For example, more than 90% of the traders in London adopt technical analysis for financial forecasting (Taylor & Allen, 1992) and a survey based in Hong Kong further underlined the popularity of technical analysis, especially in short time horizons (Lui & Mole, 1998). Furthermore, recent empirical studies have shown that the market is less efficient than was originally believed. Li and Tsang (1999) classified these supporting evidences into two main categories, namely systematic dependencies in security returns (Campbell, Lo, & MacKinlay, 1997; Jegadeesh, 1990; Lo & MacKinlay, 1990) and excess returns earned by the technical rules (Brock, Lakonishok, & LeBaron, 1992; Jegadeesh & Titman, 1993; Lehmann, 1990; Lukac, Brorsen, & Irwin, 1988; Werner, Bondt, & Thaler, 1987). These empirical studies are realizable due to the rapid development of communication and trading facilities over the past two decades, allowing financial markets to be scrutinized in greater depth than was previously impossible. The availability of high-quality and high-frequency data enabled TTS to be evaluated more accurately as compared to traditional methods of performance evaluation (Lim & Coggins, 2005). Overall, these various factors have further motivated academic interest in the development of TTS lately.

Early related works mainly revolved around the evaluation of *ad-hoc* specified TTS that are already widely used by traders (Alexander & Walks, 1961; Brock, 1992; Fama, 1970; Fama & Blume, 1966). However, these empirical studies were most likely to be spurious as such practices represent a form of data snooping due to the inherent bias in *ex-post* evaluation (Ready, 2002). The more appropriate alternative is to develop TTS on an *ex-ante* premise, for instance, evolutionary computation, a type of stochastic search technique that is widely adopted due to its capability in dealing with highly complicated search space.

One of the earliest works in evolutionary TTS (ETTS) was done by Allen and Karjalainen (1995, 1999), where genetic programming was applied to generate technical trading rules in the stock market. Subsequently, many approaches based on evolutionary computation have been proposed and applied successfully to various financial data. In most existing works, the returns generated are usually used as the sole fitness measure, without accounting for the associated risk involved. However, such an approach is

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inadequate as TTS generally spend less time in the market and its returns are less volatile as compared to the buy-and-hold strategy (Allen & Karjalainen, 1999). Furthermore, it fails to account for the different degrees of risk averseness in every individual, corresponding to different preferences between risk and returns. Neely (2003) explicitly asserted the importance of risk adjustment for the evaluation of TTS and the measure of their consistency with market efficiency (Brown, Goetzmann, & Kumar, 1998; Dowd, 2000; Jensen, 1968; Kho, 1996; Ready, 2002; Sharpe, 1966).

Ideally, TTS should have high profitability with the minimal risk possible. Unfortunately, these two criteria are inherently conflicting by virtue of the risk-returns tradeoff, where higher returns can be rendered only when subjected to a higher possibility of loss. Hence, given the underlying nature of this optimization problem, it will certainly be instructive to cast it directly into the multi-objective domain, where the risk and returns of TTS are optimized concurrently. As such, this outlines the primary motivation for this paper, where a multi-objective evolutionary platform will be constructed to investigate TTS from such a context. The evolutionary platform will maximize the total returns as per existing single-objective-based approaches, and concurrently minimizes risk, which is measured here by the proportion of trading period in the open position. Furthermore, the building blocks of the TTS will primarily comprise of popular technical indicators used commonly in real-world practices, which allows the examination of their trading characteristics and behaviors on the multi-objective evolutionary platform.

The remainder of this paper is organized as such. A brief discussion on technical trading strategy will be provided, followed by a formal introduction to the multi-objective evolutionary platform. Section 4 presents the extensive simulation result and analysis, focusing on the insights achievable under a multi-objective formulation of this problem and the investigation on the trading characteristics of the popular technical indicators used in real-world practices. Conclusions are drawn in Section 5.

2. Technical trading strategies

Traders can be broadly classified into two main categories, namely fundamentalists and technicians. Although both ultimately aim to forecast market price movements, their approaches and underlying principles differ greatly. Fundamentalists will analyze the market forces of demand and supply to determine its intrinsic value and enter (exit) the market if it is below (above) its intrinsic value, which is a sign of undervaluation (overvaluation). In stark contrast, technicians completely ignore the market fundamentals and decide solely based on market action i.e. the past history of market prices and trading action. Nevertheless, Murphy (1999) highlighted that market prices tend to lead the known fundamentals, as price movements are usually triggered by unforeseen events. As such, usually by the time the price movements is explicated, the technician are already reaping the rewards for their early entry and analyzing for exit signal. Thus, technical analysis has been the more popular choice among traders, especially in short term trades (Fyfe et al., 1999; Lui & Mole, 1998; Taylor & Allen, 1992).

Technical analysis itself can be broadly classified into two main categories: subjective and objective (Weissman, 2005). Subjective technical analysis or chart analysis focuses on the identification of specific visual patterns in the price history that corresponds to favorable market movements. However, as the visual interpretation of patterns varies between individuals, it is difficult to formalize its associated set of trading rules. On the other hand, objective technical analysis comprises of well defined rules or indicators that generate trading signal on whether to buy, sell, hold or wait. As such, their accuracy can be indisputably quantified. The ETTS considered in this paper will be solely comprised of indicators based on objective technical analysis.

Broadly, these technical indicators (TI) can be defined as such,

$$TI : \{P_t, \ldots P_{t-n+1} \rightarrow [-1, 1]\} \tag{1}$$

where $\mathrm{TI}(P_t, \ldots P_{t-n+1}) = -1$ and $\mathrm{TI}(P_t, \ldots P_{t-n+1}) = 1$ corresponds to a sell and buy trading signal respectively based on the market action, P from the current time, t to a backward period of length, n. In general, P can refer to the closing prices, highest or lowest daily prices, volume traded, etc., depending on the type of TI used. While the intervals between consecutive P, could range from daily to longer durations like weekly, monthly or even yearly (Becker & Seshadri, 2003; Iba & Nikolaev, 2000), daily trading period will be considered in this paper.

In general, a trading agent can enter the market in a long position, where the agent purchases and owns the financial asset and will profit if the price of the asset goes up, or in a short position, which refers to the practice of selling asset not owned by the seller, in the hope of repurchasing them later at a lower price. This is done so as to profit from an expected decline in price of the financial asset. The timing and type of market entry will ultimately depend on the overall trading decision of a TTS, which is in turn based on the individual signals generated from its constituent TI (Colby & Meyers, 1988; Murphy, 1999). In this paper, for a TTS compromising of a set of m TI, the various trading signals from the TI will be combined via a weighted sum and the resultant trading decisions, D, are defined as follows:

$$D : \{\mathrm{TI}_1, \ldots \mathrm{TI}_m\} \rightarrow \begin{cases} \text{Strong Buy if } T_{\text{Buy\_high}} < D \leqslant 1 \\ \text{Weak Buy if } T_{\text{Buy\_low}} < D \leqslant T_{\text{Buy\_high}} \\ \text{Hold if } T_{\text{Sell\_low}} < D \leqslant T_{\text{Buy\_low}} \\ \text{Weak Sell if } T_{\text{Sell\_high}} < D \leqslant T_{\text{Sell\_low}} \\ \text{Strong Sell if } -1 \leqslant D \leqslant T_{\text{Sell\_high}} \end{cases} \tag{2}$$

where $-1 < T_{\text{Sell\_high}} < T_{\text{Sell\_low}} < 0 < T_{\text{Sell\_low}} < T_{\text{Sell\_high}} < 1$ represents the four thresholds that governs the trader's decision with respect to the current weighted trading signal from the various TI. Specifically, the agent will enter the market in a long (short) position when the decision is strong buy (strong sell) and exit when the signal weakened to weak buy (weak sell) or worse. Also, under this definition, it is possible for an agent to switch position instantaneously, for example, an agent in a long position, originally due to a strong buy, will switch directly to a short position if D suddenly drops below than $T_{\text{Sell\_high}}$.

The following is a brief description of some of the TI widely used by real-world traders that will be used subsequently as the building blocks for the TTS. Moving average (MA) is simply the weighted average of a certain period of data and for example a simple 10 day MA of the closing prices is calculated by adding up the closing prices for past 10 days and dividing the total by 10. Other types of MA include weighted MA and exponential MA, which adopts different weight coefficients. This relationship can be generalized as follow:

$$\mathrm{MA}(t, n) = \frac{\sum_{i=t-n+1}^{t} W_i p_i}{n} \tag{3}$$

where p_i and w_i refers to the closing price and its corresponding weight at time i, while t and n denotes the current time and the length of the period considered, respectively.

MA is typically used to detect the underlying trend direction and provide the relevant trading signal. The most common approach is the double-crossover method as formulated in (4), where two MA of different periods, n_1 and n_2, are considered. Basically, if the short-term (n_1) MA is larger then the long-term (n_2) MA, it corresponds to an upward trend in the price, hence generating a buy signal and vice versa. Multiple MA crossover signals are sometimes considered also to act as alert and conformation signal (Murphy, 1999).

$$\mathrm{TI}_{\mathrm{MA}}(n_1, n_2, t) = \begin{cases} 1, & \mathrm{MA}(t, n_1) - \mathrm{MA}(t, n_2) > 0 \\ -1, & \mathrm{MA}(t, n_1) - \mathrm{MA}(t, n_2) \leqslant 0 \end{cases}, \quad n_1 < n_2. \tag{4}$$

Popular period combinations for the double crossover method are 5–20 and 10–50, though, other period has been considered also. A shorter MA, which is generally more sensitive, will trade more actively. Although earlier trading signals will thus be generated, resulting in more profitable trades, this will come at the expense of higher transaction cost and increase the likelihood of false signal. As such, the optimal parameter setting should allow the TI to possess a certain degree of sensitiveness so as to react immediately to market movements and be yet unsusceptible to false signals.

Relative strength index (RSI), a popular price momentum oscillator, measures the strength of market movement by comparing the magnitude of its recent gains to the magnitude of its recent losses and it can be mathematically expressed as such,

$$\mathrm{RSI}(t, n) = 100 - \frac{100}{1 + RS}, \quad \mathrm{RS} = \frac{AG}{AL} = \frac{100 \times AG}{AG + AL} \tag{5}$$

where RS is calculated as the ratio of two exponentially smoothed moving averages, *AG/AL*. *AG* and *AL* are, respectively the average price gain and price drop from the current time, t to a backward period of length, n. Similarly to MA, a shorter time period will result in oscillations of higher frequency and amplitude, increasing its sensitivity to market movements.

RSI will typically oscillate within the range between 0 and 100, reflecting the market condition and the popular interpretation of RSI is to look for oversold levels below a specified low threshold (*Low*) and overbought levels above a specified high threshold (*High*), which can be formalized into the technical rule in (6). Trading signal will be generated when the RSI exceeds either threshold, otherwise it will correspond to a holding signal of 0.

$$\mathrm{TI}_{\mathrm{RSI}}(n, t, High, Low) = \begin{cases} 1, & \mathrm{RSI}(t, n) < Low \\ 0, & Low < \mathrm{RSI}(t, n) < High \\ -1, & RSI(t, n) > High \end{cases} \tag{6}$$

Stochastic oscillator (SO) is a momentum or price velocity indicator that measures the position of a stock compared with its most recent trading range. Specifically, it measures the relationship between the closing price, *CL* of a stock and its highest high, *HH* and lowest low, *LL* from the current time, t to a backward period of length, n.. The underlying rationale is that closing prices near the top of the range implies accumulation (buying pressure) and those near the bottom of the range indicate distribution (selling pressure). As such, reading below the specified low threshold or above the specified high threshold corresponds to an oversold and overbought market; hence the appropriate decision signal will be generated. This raw stochastic value is denoted as *%K*, which is then smoothed with a simple moving average to produce *%D*. There are several ways to interpret SO and one of the popular methods is described as follows. Basically, *%D* will be the 3 day moving average of *%K* and similar to RSI, trading signal will be generated when both *%D* and *%K* exceeds either threshold, otherwise it will correspond to a holding signal of 0.

$$\%K(t, n) = 100 \times \frac{CL(t) - LL(t, n)}{HH(t, n) - LL(t, n)} \tag{7}$$

$$\%D = 3 \text{ Period Moving Average of } \%K$$

$$TI_{SO}(n, t, High, Low) = \begin{cases} 1, & \%K, \%D < Low \\ -1, & \%K.\%D > High \\ 0, & \text{or otherwise} \end{cases} \tag{8}$$

while the various TI, discussed so far, have been used extensively in the financial market as a decision tool for investors or by economists to explain market phenomena, their underlying characteristics have not been fully explored before in the context of evolutionary platform. As such, the multi-objective evolutionary platform that will be introduced in the next section will evolve TTS based on these TI as the building blocks and investigate their trading characteristics, particularly their frequency in generating trading signals and their level of participation in the market.

3. Multi-objective evolutionary platform for ETTS

Evolutionary computation is a class of stochastic search technique that has been gaining significant attention from the research community in the recent years for its success in solving real-world problems that are inherently complex with various competing specifications. The EA paradigm is largely inspired by the biological process of evolution, where potential solutions are encoded as chromosomes to epitomize the mechanics of DNA blueprint of living organisms, so as to allow the inheritance of desirable properties to offspring solutions and the propagation of information through genetic variation. The primary advantage of ETTS is that a resolute definition of the general form for the trading rules is not required and the search can be conducted efficiently in a non-differentiable space of rules (Neely et al., 1997) on an *ex-ante* approach. This section presents the multi-objective evolutionary platform that will be used for the optimization of ETTS. The various features of the evolutionary platform will be introduced in turn before describing its overall algorithmic flow.

3.1. Variable-length representation for trading agents

Depending on the representation and the evolutionary operators, evolutionary computation can be further classified into genetic algorithm, genetic programming, evolutionary strategies and evolutionary programming, with the former two being the more popular approach for the optimization of ETTS. The main difference between genetic algorithm and genetic programming lies in their representation. The former adopts pseudo-chromosomal (binary) strings to encode the information describing the underlying ETTS. The encoded information can be a masking string to include/exclude the use of certain TI (Korczak & Roger, 2002; Wang & Chen, 1998) or a direct parameter encoding of its constituent TI (Jangmin, Lee, Lee, & Zhang, 2005; Jiang & Szeto, 2003; Lim & Coggins, 2005; Lin, Cao, Wang, & Zhang, 2004; Schoreels & Garibaldi, 2005; Schoreels, Logan, & Garibaldi, 2004). On the other hand, genetic programming uses hierarchical variable-length strings symbolizing decision trees. The non-terminal nodes could be arithmetic, Boolean or conditional function and the terminal nodes could be variables or constant that serves as arguments of the functions (Allen & Karjalainen, 1999; Chen & Yeh, 1997; Fyfe et al., 1999; Li & Tsang, 1999; Neely et al., 1997).

The former representation is simple and straightforward and because of the fixed structure, the underlying trading rules are easily interpretable. However, since the chromosomes are constrained to certain pre-defined structures, the novelty of the TTS evolvable will be limited. While this is not an issue in the tree-based representation in genetic programming, the complexity of its search space might be too high for efficient optimization and the evolved solutions are often plagued with redundancy (Allen & Karjalainen, 1999; Garcia-Almanza & Tsang, 2006). Considering their fair share of advantages and limitations, the chromosomal representation adopted actually represents a hybrid between these two representations.

In real-world practices, technical investors usually based their trading decision on a set of TI with varying degree of preferences.

Their parameters will consistently be tweaked and tuned based on the trader's experience and their past performance of the corresponding TI. To emulate such characteristics in the evolutionary platform postulated, trading agent are modeled as a set of decision thresholds and TI of different weights and parameters (defined in (2)) that will govern its trading activity, as illustrated in Fig. 1. Adopting such a variable-length chromosomal representation (Cheong, Tan, & Veeravalli, 2007; Tan, Cheong, & Goh, 2007; Tan, Chew, & Lee, 2006), TI could be added and removed from the trading agent during the evolutionary process to adapt to the market conditions. Apart from possessing such flexibility, the underlying trading rules associated with each trading agent are comprehensible. The weights associated with each TI indicates its relative importance in influencing the overall trading activity, where the trading decision at every time step is simply the weighted average of the decision signals from the various TI. Further details will be discussed in the later sections.

The description for the various genes in the variable-length chromosome is summarized in Table 1. The trading agents will build their strategies based on these three different TI and due to the variable-length chromosomal structure, TI of the same type can exist together in a single chromosome. Essentially, the optimization process involved finding an optimal combination of TI with appropriate parameters and weights.

3.2. Multiple objectives

In related literature, the fitness/optimality of ETTS is either measured by the accuracy of the predictions made (Li & Tsang, 1999; Mahfoud & Mani, 1996; Tan, Quek, & Ng, 2005) or solely based on its profitability. As the former is more applicable for classification problem, the latter represents the more intuitive choice for performance evaluation. Even so, the latter could be measured in different ways, for example, the total asset, namely the available capital and the value of all holdings, at the end of the trading period (Kendall & Su, 2003; Wang & Chen, 1998) or the area under the total asset graph during the trading period (Schoreels & Garibaldi, 2005). In other cases, the generated profits are directly pegged to those generated by the buy-and-hold strategy (Allen & Karjalainen, 1999; Fyfe et al., 1999). However, all these measures failed to acknowledge the risk involved with the trading activity (Neely, 2003). As such, performance measures like Sharpe ratio or Sterling ratio was proposed instead, which can measure the net profitability after discounting the associated risk (Korczak & Lipinski, 2004; Neely, 2003).

Clearly, the optimization of ETTS involves a delicate balance between its expected returns and associated risk. As such, contrary to conventional single-objective approaches, where the risk is completely ignored or the two conflicting objectives of risk and returns are combined into one single measure known as the risk-adjusted profit, this paper will model the problem directly as a multi-objective optimization problem by simultaneously optimizing the returns and risk of the ETTS.

Considering a period of length T, corresponding to a total number of n trades, the total returns for the period is defined as such,

$$\text{Maximize } F_1: \text{ Total Returns} = \sum_{i=1}^{n} K \cdot P_{i,\text{exit}} / P_{i,\text{entry}}, k = \begin{cases} 1, & \text{long entry} \\ -1, & \text{short entry} \end{cases} \tag{9}$$

where $p_{i,\text{entry}}$ and $p_{i,\text{exit}}$ denotes the price at which the trading agent enter and exits the market, respectively for the ith trade and the multiplier, k is to adjust the returns to compensate for the different type of entries i.e. a depreciation in asset prices actually corresponds to a profit for a short entry. In essence, this objective function simply measures the arithmetic total of the percentage price changes for all the trades made in the trading period. The arithmetic total is considered here instead of the mean, as a profitable trading rule may forecast rather poorly much of the time, but perform well overall because it is able to position the trader on the right side of the market during large moves (Neely et al., 1997). Also, the use of percentage changes removes the dependence on entry prices as compared to absolute value difference. Lastly, this measure accounts entirely for the profitability and avoids the need to define the order size for each trade.

Risk is defined as the volatility or the uncertainty of the expected returns over the trading period. For instance, a TTS that yield returns ranging between 4% and 6% is less volatile than one, whose returns ranges between −40% and 50%, even though their average returns is the same. Standard risk measures like variance or semi-variance are not suitable in this paper. The former fails to consider that investors are more averse to negative deviations about the mean returns as compared to positive returns (Bernstein & Damodaran, 1998); while the latter is somehow correlated to the returns i.e. minimizing the semi-variance will indirectly maximize the total returns. In fact, preliminary investigation that considers them as the risk measure failed to obtain a Pareto front that could accurately depicts the risk-returns tradeoff.

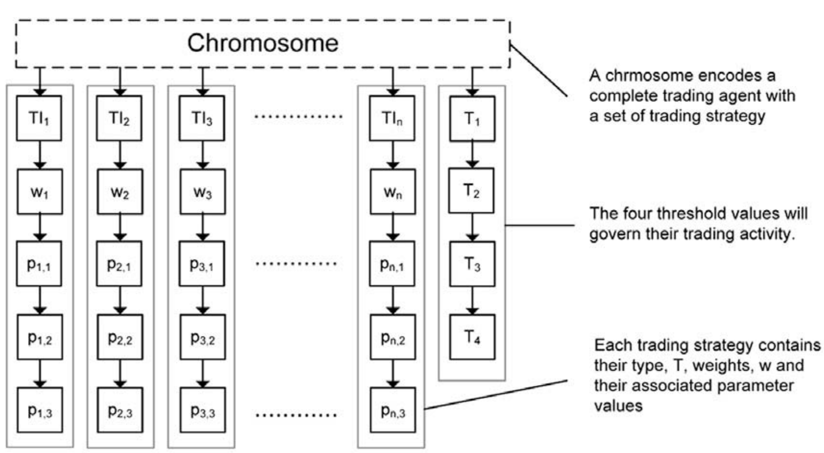

Fig. 1. Variable-length chromosomal representation for the trading agents, which essentially comprised of a weighted combination of a set of commonly-used TI in real practices.

Table 1
Gene description of the various parameters (general and TI-specific) being optimized.

Technical indicator	Parameters	Range
MA	Short term period	[1,50]
	Long term period	[1,50]
RSI	Period	[1,40]
	RSI selling threshold	[1,50]
	RSI buying threshold	[50,100]
SO	Period	[1,40]
	SO selling threshold	[1,50]
	SO buying threshold	[50,100]
–	Weights	[0,−1]
–	Decision sell threshold	[−1,0]
–	Decision buy threshold	[0,1]

Instead, risk will be defined here by the trader's exposure to it. Specifically, it will be measured by the proportion of trading days when an open position is maintained in the market (Weissman, 2005) and is mathematically formulated as such,

$$\text{Minimize } F_2 : \text{Risk Exposure} = \frac{1}{T}\sum_{i=1}^{n}(t_{i,\text{exit}} - t_{i,\text{entry}}) \tag{10}$$

where $t_{i,\text{entry}}$ and $t_{i,\text{exit}}$ denotes the time at which the trading agent enter and exits the market, respectively for the ith trade and T refers to the total length of the trading period. Essentially, staying longer in the market corresponds to a higher exposure to risk like catastrophic events and market crashes while a shorter period, which is associated with lower risk exposure, will corresponds to higher liquidity as the available capital is tied up for a lesser time. Such an optimization function will be in conflicting nature with returns, as higher total returns are usually associated with higher degree of trading activity, which naturally leads to a longer periods of open position. Even though risk exposure is being considered here, this measure will, at times, be conveniently referred to as risk in this paper.

3.3. Fitness evaluation

The fitness evaluation process is concerned with calculating the total returns and risk exposure associated with each trading agents in the evolving population. During the stipulated trading period, each TI of the trading agent will generate trading signals on a daily basis based on the current and historical market actions. The overall trading decision to buy, sell or hold is obtained by considering the weighted sum of the various individual signals and the decision threshold of the trading agents. The corresponding fitness values of the trading agent can be subsequently calculated once the trading schedule is determined.

For a clearer illustration, let's consider an instance of the variable-length chromosome (Fig. 2) being applied to a hypothetical price series (Fig. 3) comprising of 250 trading days. The TTS involved comprises of the three different TI and their respective trading signal within the entire trading period is illustrated in Fig. 4. For MA in Fig. 4a, a buy signal of 1 will be generated if the difference is positive and conversely, a sell signal of −1 will be generated, when the MA difference i.e. $\text{MA}(t, n_1) - \text{MA}(t, n_2)$ falls below zero. For RSI and SO, buy signal and sell signal will be generated when they exceed the buying threshold or fall below the selling threshold respectively. Otherwise, it will correspond to a hold signal of 0.

Clearly from the plots in Fig. 4, trading signals from the various TI are different in terms of the trade frequency and duration. MA tends to generate longer buy and sell signal due to the nature of its definition, while SO generated shorter buy and sell signal but at a higher frequency. Also, due to the high RSI buying threshold,

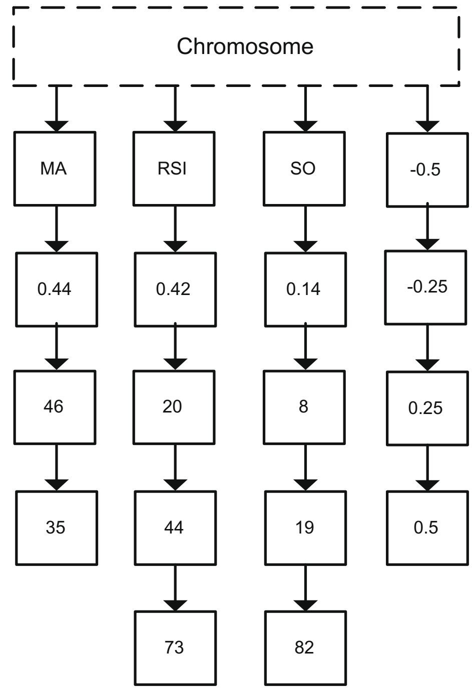

Fig. 2. An instance of the variable-length chromosome comprising of the three different TI i.e., MA, RSI and SO.

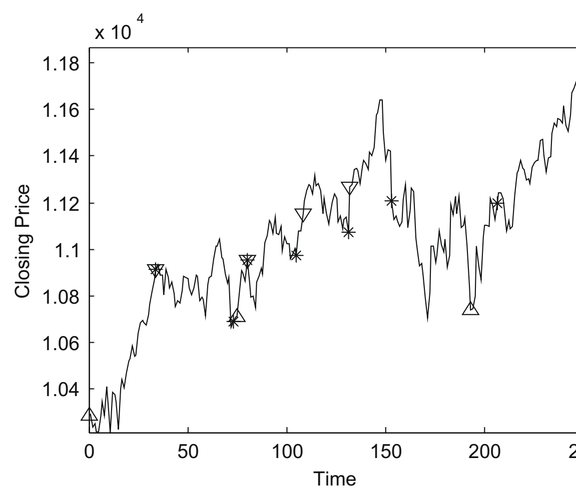

Fig. 3. Hypothetical price series comprising of 250 trading days. Trading activity determined in Fig. 5 is included where upward triangle, downward triangle and asterisk denote long entry, short entry and exit, respectively.

no buy signals were generated from RSI. A more in-depth analysis on the characteristic of the various TI will be conducted in Section 4.

The overall decision signal, which is the weighted sum of its constituent trading signals, is illustrated in Fig. 5. The trading agent will enter the market in a long position, whenever the decision signal goes above $T_{\text{Buy\_high}}$ of 0.5, denoting a strong buying signal. Correspondingly, it will exit anytime the decision signal falls below $T_{\text{Buy\_low}}$ of 0.25, as the buying signal has weakened. Short sell, which is considered also in this model, will be executed vice versa, based on $T_{\text{Sell\_high}}$ and $T_{\text{Sell\_low}}$.

It should be highlighted that, for simplicity in the trading model, it is assumed that the trading environment is a discrete and deterministic liquid market, where the price is unaffected by the agents' actions. The trading schedule of the agent is tabulated as

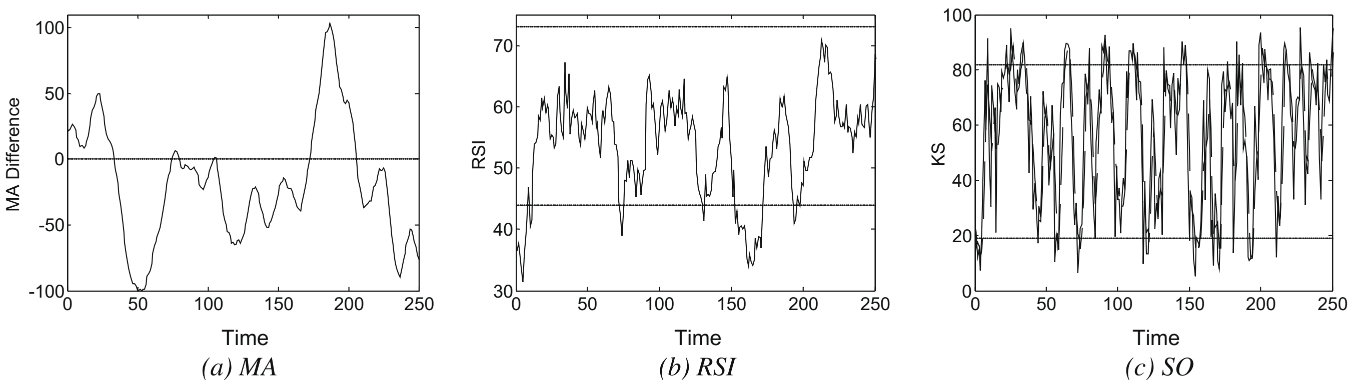

Fig. 4. Traces of the trading signals generated by the various TI over the trading period. The respective thresholds of RSI and SO are denoted by the horizontal dotted lines.

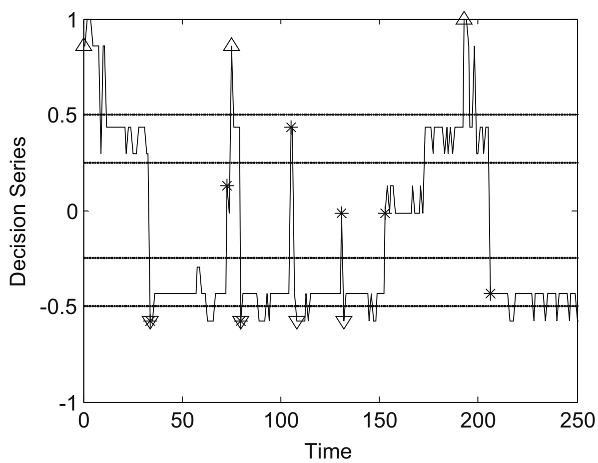

Fig. 5. Trace of the overall trading signal (Upward triangle, downward triangle and asterisk denote long entry, short entry and exit, respectively). The respective thresholds are denoted by the horizontal dotted lines.

follow. Altogether, the agent performed seven trades within this period. While there are no limits on the number of trades conducted, each complete trade will be subjected to a fixed transaction cost of 0.5% to simulate brokerage charge, interest rate, liquidation costs or other form of costs.

The calculation of returns and risk associated with the trading agent shown in Fig. 2 is tabulated in Table 2. As mentioned earlier, the arithmetic total of each percentage gains net of transaction cost and the proportion of days in open position are used to quantify the total returns and risk exposure respectively. In this particular example, the corresponding fitness values are calculated to be 12.35% and 0.64, respectively.

3.4. Pareto fitness ranking

Evolutionary optimization of TTS is cast as a multi-objective problem in this paper, which involves the maximization of the total returns and minimization of risk exposure. In contrast to single-objective optimization, the optimal solutions to a multi-objective optimization problem exist in the form of alternate tradeoffs known as the Pareto-optimal set. Each objective component of any non-dominated solution in the Pareto-optimal set can only be improved by degrading at least one of its other objective components. The Pareto-optimal set when plotted will constitute the risk-return tradeoff or Efficient Frontier as illustrated in Fig. 6.

Each point denotes a TTS evolved by the MOEA and the black and gray circles represents non-dominated and dominated solutions respectively. The former set is the Pareto optimal solution as their returns cannot be improved further without compromising risk. In the context of single optimization of ETTS where returns is the sole priority, the evolutionary process will ultimately drive the solutions towards the extreme point B. This is not applicable for conservative investors, who prefer lower risk as compared to higher returns. Point A represents the extreme case of a conservative investor with zero returns due to an empty trading schedule.

In the total absence of information regarding the preference of objectives, the Pareto ranking scheme is considered to represent the fitness of each trading agent in such a context. Specifically, this scheme assigns a default minimal ranking for all the non-dominated solutions, while the dominated solutions will be ranked according to how many other solutions in the population dominate them. The rank of a solution, i, in the population is

$$\mathrm{Rank}(i) = 1 + n_i, \tag{11}$$

where n_i is the number of ETTS dominating the ith ETTS in the population pool.

Table 2
Trading schedule of the agent in Fig. 2 and the calculation of its total returns and risk exposure with the trading period.

Trade no.	Trade type	Entry time	Exit time	Trading period	Entry index	Exit index	Returns (%)	Net returns (%)
1	Long	0	34	34	10,287	10,916	6.11	5.61
2	Short	34	73	39	10,916	10,689	2.08	1.58
3	Long	75	80	5	10,710	10,954	2.28	1.78
4	Short	80	105	25	10,954	10,972	−0.16	−0.66
5	Short	108	131	23	11,151	11,074	0.69	0.19
6	Short	132	153	21	11,269	11,206	0.56	0.06
7	Long	193	206	13	10,739	11,200	4.29	3.79
			Total proportion	160/250 = 0.64		Total returns	15.85	12.35

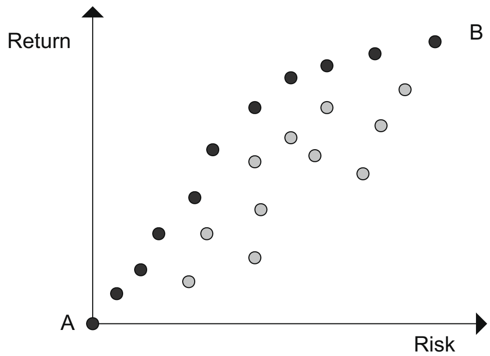

Fig. 6. Illustration of the risk-returns tradeoff.

3.5. Variation operation

As standard chromosomal representation with well-established variation operators were not considered here, specific operators need to be designed for this purpose. In evolutionary algorithm, good combinations of genes are exchanged between different chromosomes of the population via crossover operators. The crossover operator adopted for the variable-length chromosome is illustrated in Fig. 7. Essentially, the crossover operation involves combining the TI for the two parent chromosomes and randomly distributing them amongst the two child chromosomes. The threshold values will be inherited directly during the process.

The crossover operation will be complemented by a multi-mode mutation operator (Tan et al., 2006, 2007) in allowing a larger search space to be explored. The primary motivation for such an operator is that the variable-length chromosome adopted has varying hierarchy, in terms of the different type of indicators and their corresponding weights and parameters. As such, the multi-mode mutation operator is to cater for such data structure and allow the variable-length chromosome to be altered at varying levels.

Each mode represents varying degree of perpetuation in the search space and thus signifies different exploration and exploitation efforts. The various modes are as such:

1. *Indictor level*: At random, an existing TI is being removed from the trading agent or a random indicator is being initialized and added to it.
2. *Parameter level*: A TI is being chosen at random and its parameters are subjected to Gaussian mutation.
3. *Threshold level*: The various TI remain unchanged, while the four threshold values are subjected to Gaussian mutation.

These three different modes will be invoked randomly during the mutation operation.

3.6. Algorithmic flow

The algorithmic flow of the multi-objective evolutionary platform is shown in Fig. 8. At the start of the algorithm, the decision signals of the TI under all possible parameter configurations are

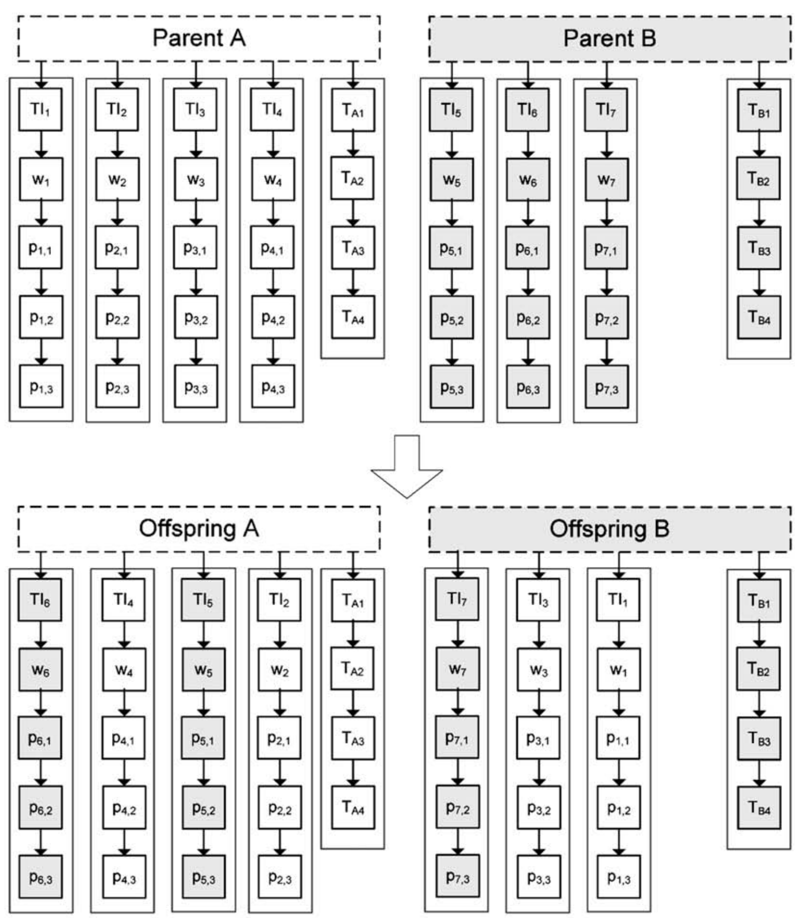

Fig. 7. Illustration of the trade-exchange crossover.

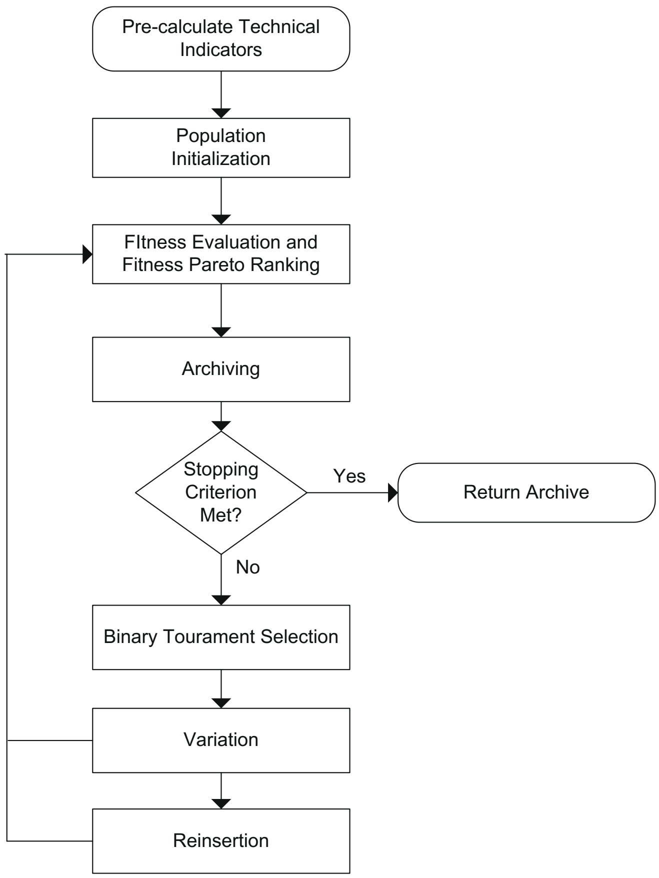

Fig. 8. Algorithmic flow of the multi-objective evolutionary platform.

pre-calculated. This allows direct access of this information during algorithmic runtime, which will speed up the computation time required.

- *Initialization*: The algorithm maintains a fixed size population throughout the evolutionary process. During the initialization process, trading agents will be randomized until the population is filled. Specifically, it will involve randomly generating a number of TI within a predefined range of random weights and parameters.
- *Elitism*: Although multi-objective evolutionary algorithms have been implemented in many different ways, most current state-of-the-art works in general encompasses some form of elitism in both the archiving and selection process. A fixed size archive is used to store the non-dominated solutions discovered during the evolutionary process. The archive is updated every generation, where agents that are not dominated by any members in the archive will be added into the archive and any members in the archive that are dominated by this new agent will be removed. The archive helps to ensure convergence by preventing the loss of good solutions due to the stochastic nature of the evolutionary process. In the selection process, elitism is implemented by selecting individuals to a mating pool through a binary tournament selection of the combined archive and evolving population. The selection criterion is based on Pareto ranking and in the event of a tie, the niche count will be employed. The mechanism of niche sharing is used in the tournament selection as well as diversity maintenance in the archive.
- *Reinsertion*: Randomly generated trading agents are added to the evolving population every generation to complement the variation operation. This allows greater exploration of the search space and prevents premature convergence by introducing genetic materials that are not formally present in the initial gene pool. This approach is similar to immigration (Branke, 1999; Schoreels & Garibaldi, 2005), but the latter directly replaced the mediocre proportion of the populations by these new solutions. Such an approach is avoided as the ordering of solutions in multi-objective optimization is not so straightforward.

After one complete generation, the evolutionary process will repeat until a predefined number of generations are reached.

4. Experimental results and analysis

The viability of the multi-objective evolutionary platform and the TTS evolved will be studied in this section. The effectiveness of hybridizing multiple TI to form TTS will be investigated first, followed by an assessment of the generalization performance of the ETTS evolved. The performance of the ETTS will be compared against the buy-and hold strategy – a long term investment strategy where stocks are bought and held for a long period regardless of the market's fluctuations. The argument for this strategy is actually the Efficient Market Hypothesis (Fama, 1970), whereby if every security is fairly valued at all times, then there is really no incentives to trade. This underlying principle behind the buy-and hold strategy is a stark contrast as compared to that of technical analysis.

The financial data considered in the various experimental studies are the daily trading data of the Straits Times Index (STI), a market value-weighted stock market index that is based on the stocks of 50, representative companies listed on the Singapore Exchange. A total of 3368 trading days were considered, which span from the period 11-08-1992 to 30-12-2005. However, the actual number of trading data used will differ in the various experiments.

The parametric configurations of the multi-objective evolutionary platform outlined in section III are summarized in Table 3. These parameters have been selected based on a series of preliminary investigation and parameter tuning. A reinsertion ratio of 0.1 denotes that 10% of the children chromosome at every generation will comprise of randomly generated trading agents, with the remainder coming from the variation operation. 20 independent runs were made for each experimental study with each set of runs having the same random seed to ensure the same initial population.

4.1. Performance comparison between individual TI and hybrid TI

Many different types of TI had been considered in previous related works on ETTS and the exact quantity constituting the trading agent can easily vary from one (Jiang & Szeto, 2003) to even hundreds (Korczak and Lipinski, 2004). Despite so, the effects of hybridizing several TI as opposed to applying them individually in constructing TTS have never been studied in-depth before. Thus, this section will investigate whether the hybridization of TI are synergetic or destructive in nature. For this purpose, different combinations of the three TI were considered as listed in Table 4 and the same evolutionary platform was adopted with the only difference being the type of TI available as the building blocks for the trading agents during the evolutionary process. For example, ETTS evolved by D1 will only comprise of MA and RSI, but not SO.

The trading agents are optimized based on a four year financial data from the period 02-01-2002 to 30-12-2005 as plotted in Fig. 9. About 100 days of historical data prior to the first trading days are included also, as some TI need a certain amount of historical data in their calculations. Fig. 10 plots the Pareto fronts evolved by some of the TI combinations in one of the experimental run. While the various solutions sets are of varying optimality in terms of Par-

Table 3
Parameter settings of the multi-objective evolutionary platform used in the experimental study.

Parameter	Values
Population size	100
Generation	1000
Crossover rate	0.8
Mutation rate	0.1
Reinsertion ratio	0.1
Maximum number of technical indicators in a trading agent	10
Number of experimental runs	20

Table 4
Different combinations of TI used to assess the hybridization of TI in the trading agents.

Combination description	Notation
MA only	MA
RSI only	RSI
SO only	SO
MA and RSI	D1
MA and SO	D2
RSI and SO	D3
MA, RSI and SO	ALL

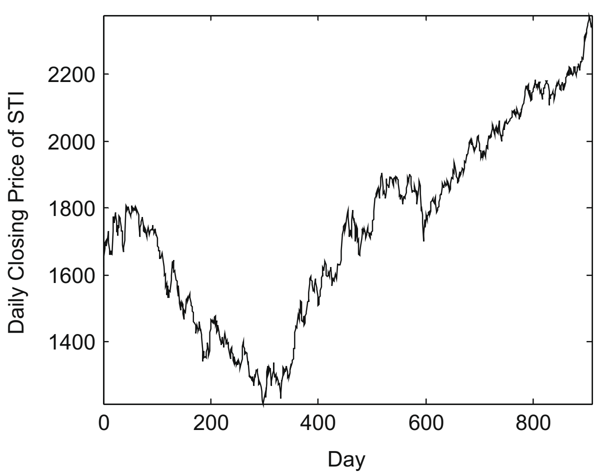

Fig. 9. Daily closing prices of STI used for the optimization of the ETTS.

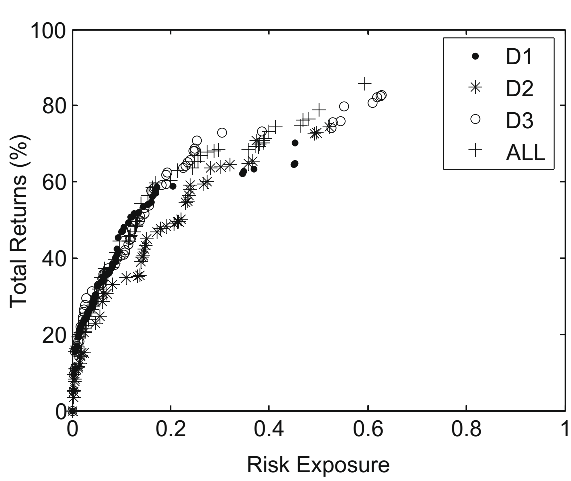

Fig. 10. Pareto fronts obtained by the selected TI combinations in one of the experimental runs.

eto dominance, they clearly illustrate the inherent tradeoff between total returns and risk exposure. Also, the trading agents evolved are able to generate high returns in open positions less than 100% of the trading period, i.e. total returns above 80% with risk exposure around 0.6 by ALL. Comparatively, the total return of the buy-and-hold strategy is only 44% during this period. Clearly in this context, the buy-and-hold strategy is suboptimal.

Considering discrete intervals of 0.1 for risk exposure, Fig. 11 plots the distribution of the average returns and number of trading agents along the Pareto front obtained by ALL in the 20 experimental runs. The risk-returns tradeoff is again evident in Fig. 11a, where the average returns increases for higher level of risk exposure. The sudden drop in average returns after risk exposure of 0.8 can be attributed to the lack of solutions in that region, as illustrated in Fig. 11b. In fact, the evolved Pareto front is not uniform as there is a higher density of solutions at the lower risk-returns region. The non-uniformity could be due to the general difficulty in finding TTS that can fully exploit all the price movements and generate exceptionally high returns in the presence of transaction cost.

Of course, a visual comparison of the Pareto front is not adequate for a complete performance assessment between the various combinations. Binary quality measures, which compare the dominance relationship between pairs of solutions sets, should be adopted (Zitzler, Thiele, Laumanns, Fonseca, & Fonseca, 2003). For this purpose, the coverage function (C) (Zitzler & Thiele, 1999) is included, which gives for a pair of solutions sets (A, B) the fraction of solutions in B that are weakly dominated by one or more solutions in A. The value $C(A, B) = 1$ means that all the points in B are dominated by, or equal to the points in A. The opposite, $C(A, B) = 0$ represents the scenario, when none of the points in B are covered by the set A. It should be highlighted that both $C(A, B)$ and $C(B, A)$ have to be considered for a complete performance assessment.

The coverage metrics represent quantitative measures that describe the quality of the evolved solution and they are illustrated in box plots in Fig. 12 to provide the statistical comparison results. The thick horizontal line within the box encodes the median while the upper and lower ends denote the upper and lower percentile, respectively. Dashed appendages illustrate the spread and shape of distribution and crosses represent extreme values.

From the boxplots, the hybrid combinations are clearly better than the individual combinations where the agents evolved by the former are able to Pareto-dominate a larger percentage of those generated by the latter in terms of higher returns at a lower risk exposure. Also, the performance difference between ALL and the individual TI combinations are much more significant than that of ALL and the dual TI combinations. This seems to suggest some form of diminishing marginal benefits in considering more TI in the construction of TTS. As such, in this context, excessive TI should be avoided, which could also help to maintain the complexity of the search space. Of course, further experimental studies involving other types of TI should be conducted to validate this hypothesis.

Amongst the individual TI, RSI has the best performance in coverage, as it is able to dominate a larger proportion of the solutions evolved by MA and SO, yet having a small proportion of its solution being dominated by them as observed from Fig. 12a–c. This relationship is similarly observed for the dual combinations, where D1 and D3 which comprised of RSI perform much better than D2. Nonetheless, statistical analysis reveals no significant performance difference between D1 and D3.

The two main goals in multi-objective optimization include proximity and diversity (Bosman & Thierens, 2003; Deb, 2001), where the former describes the accuracy of the solution set and the latter measures how well the solution set is defined. While the coverage function compares the proximity relationship between the various combinations, it is also necessary to assess their diversity relationship by measuring the extent in which the opti-

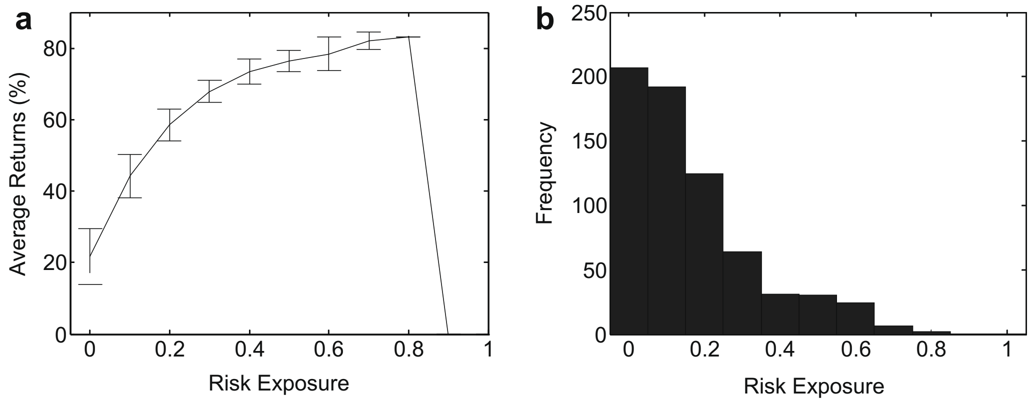

Fig. 11. (a) Average returns and (b) number of trading agents in discrete intervals of Risk Exposure of 0.1 that were generated by ALL in the 20 experimental runs. The vertical line in (a) indicates the standard deviation of the returns at each discrete level of risk exposure.

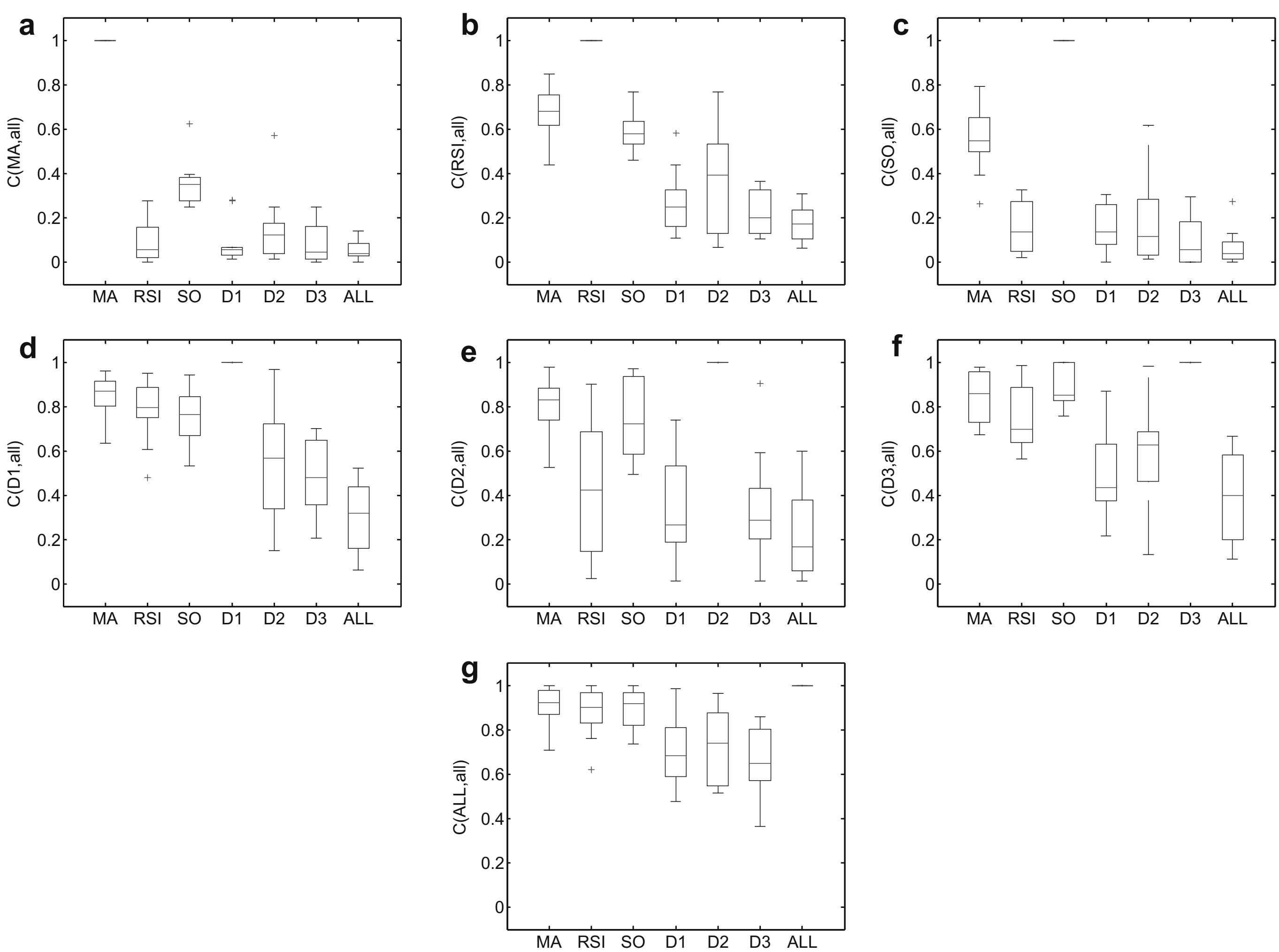

Fig. 12. Box plots illustrating coverage relationship between the various TI combinations schemes.

mal Pareto front is covered by the evolved solutions as in the maximum spread measure (Zitzler, Deb, & Thiele, 2000). Of course, Maximum spread is only applicable for benchmark optimization problems where the optimal Pareto front is known. Thus, an alternative measure is proposed here, which simply computes the area in the objective search space covered by the solution sets.

$$\text{Spread} = (\text{return}_{\max} - \text{return}_{\min})(\text{risk}_{\max} - \text{risk}_{\min}) \quad (12)$$

The boxplots in Fig. 13 illustrates the average spread for the various TI combinations in the 20 experimental runs. Interestingly, RSI, which attained better performance in Pareto dominance amongst the individual strategy, has the lowest spread. On the contrary, D2, which do not include RSI in its composition, attained the highest spread amongst the various combinations. This seems to suggest that different TI is instrumental in attaining solutions at different regions of the risk-return tradeoff. Fig. 14 compares the Pareto

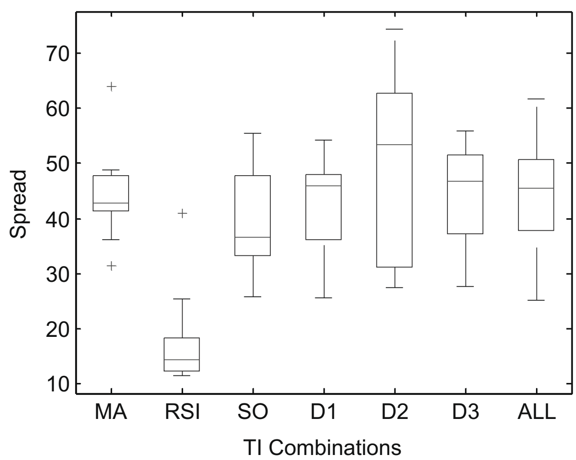

Fig. 13. Box plots illustrating Spread obtained under the various TI combinations schemes.

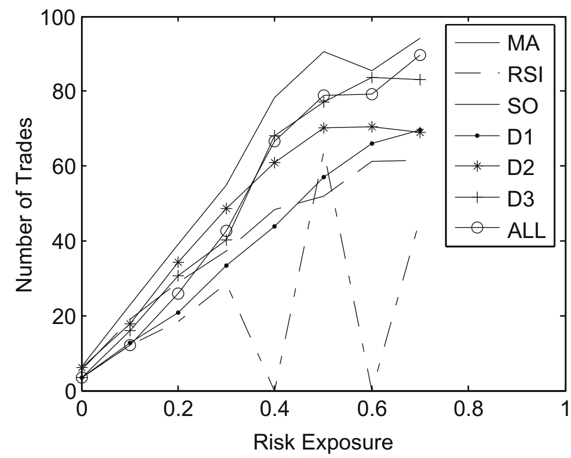

Fig. 15. Average number of trades by the trading agents in discrete intervals of risk exposure of 0.1 that were generated by the various TI combinations in the 20 experimental runs.

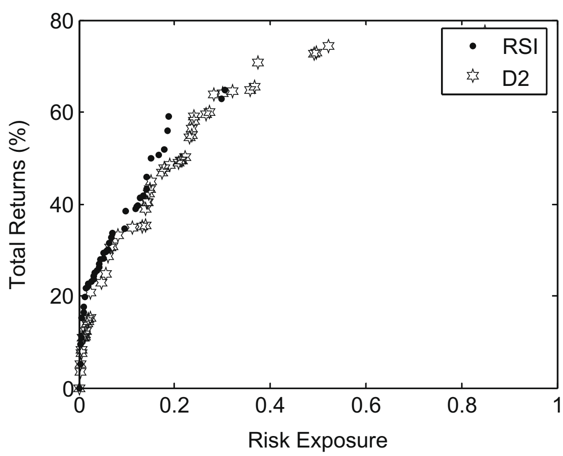

Fig. 14. Pareto fronts obtained by RSI and D2 in one of the experimental runs.

fronts attained by RSI and D2 in one of the experimental and it corresponds accurately to the experimental results so far i.e. D2 was able to diversify over a larger area of the objective but most of its evolved solutions were dominated by RSI in the low risk-returns region.

To shed light on the underlying differences between the various TI, Fig. 15 plots the mean number of trades versus risk exposure for the various TI combinations considered. ETTS, comprising of MA and/or SO, trade more actively as compared to those consisting of RSI. These characteristics are actually elucidated by their trading signals in Fig. 4 also. Comparatively, SO generates buy and sell signals at a higher frequency and MA, which, does not have any holding signal at all, tend to remain at an open position in the market. Also, it is observed that all combinations except RSI have a stable uptrend. One possible explanation is that the solutions generated by RSI are overly concentrated in the low risk region, resulting in erratic behavior in the high risk region.

The experimental results so far seem to suggest that RSI aids better in low risk trading, while MA and SO are more prominent in high risk trading. This is most probably due to the latter's higher tendency to generate buy/sell signal, increasing the possibilities to generate active trading schedule of greater risk exposure and returns, which will consequently results in higher spread. To further affirm the trading characteristics of the TI, it will certainly be instructive to investigate the composition of the various TI in the chromosomes evolved by ALL. Fig. 16 plots the average weight and frequency of the various TI in each ETTS obtained by ALL. As the type of TI available is lesser than the maximum TI allowable for each agent, there could be multiple instances of the same TI in a single ETTS. Clearly, SO constitutes the largest proportion both in terms of the weights and frequency.

Lastly, to analyze how the composition of TI in the trading agents changes along the risk-returns tradeoff, Fig. 17 plots the average weights of the various TI for each trading agent against their corresponding risk exposure. Clearly from Fig. 17b, there is a higher density of solutions in the low-risk region as compared to the high-risk region. This further reinforces the earlier claims that associate RSI with conservative trading schedules. To illustrate clearer the composition changes along the risk-returns tradeoff, interval of 0.1 for the training risk is considered and the mean and standard deviation of the weights at each interval is plotted in Fig. 18. As expected, RSI, which is associated with conservative trading schedules, has higher weights at lower risk, while MA is more prominent in active trading schedules, where its average weight increases for higher risk. Lastly, Fig. 18c illustrates that SO forms a significant proportion of the ETTS at the various risk level, which again could be explained by its balance between the proximity and diversity goals (see Fig. 18).

The various experimental results show that the composition of TI along the risk-returns tradeoff is related to their underlying characteristics. As such, the non-uniformity in the risk-returns tradeoff, where the diversity of solutions decreases at higher level of risk (Fig. 11b), could be due also to the lack of TI that can generate highly active trading schedules. Thus, more TI should be included in future related studies. Also, it will be useful to profile these TI for a better understanding of their trading operation. This information could be useful in the development of local search operators that can exploit their underlying characteristic, so as to improve the algorithmic convergence of the evolutionary platform.

4.2. Correlation analysis between training and test performance

The experimental results earlier revealed the trading characteristics of the TI constituting the ETTS. Despite the high returns generated by the ETTS at various level of risk exposure, the practicality of this approach will ultimately depend on whether these high returns can be extended to unseen trading data, which is otherwise known as its generalization performance.

To evaluate its generalization performance, the historical financial data used for the training and evaluation of ETTS earlier will be

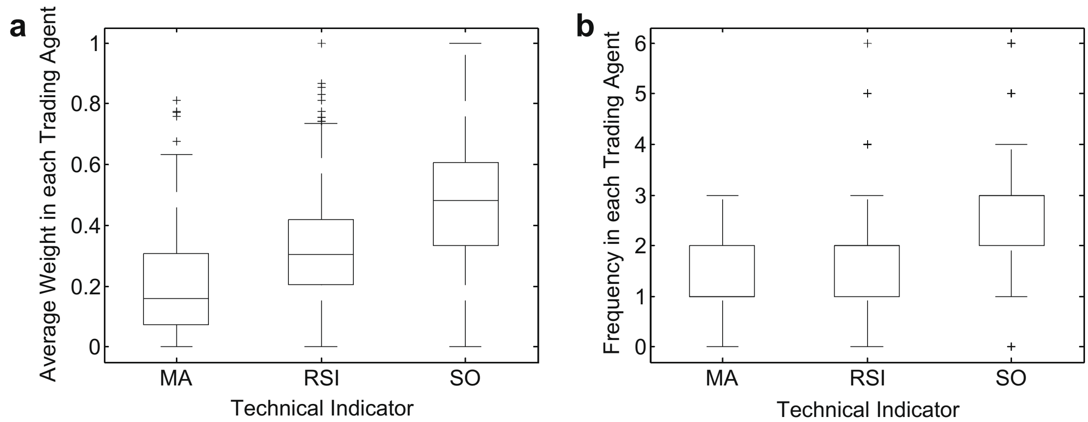

Fig. 16. (a) Average weight and (b) frequency of the individual TI in each trading agent evolved by ALL.

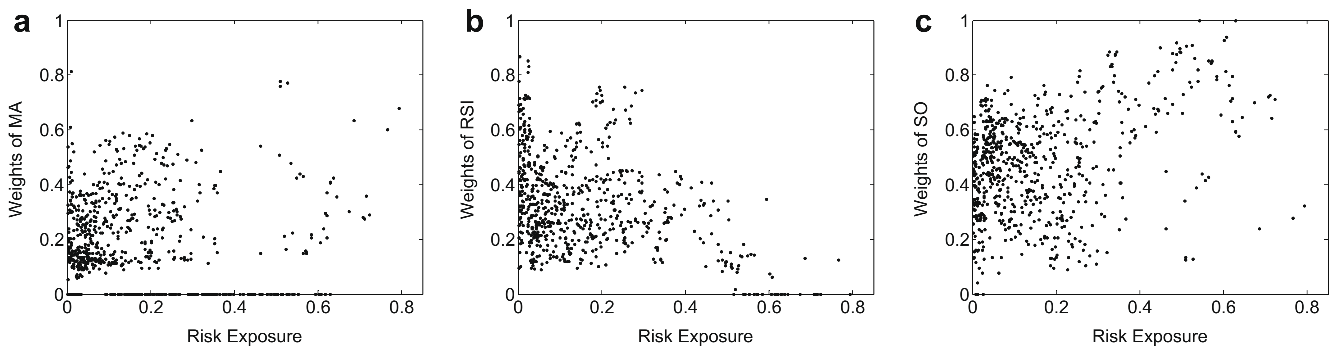

Fig. 17. Average weight of (a) MA, (b) RSI and (c) SO in each trading agents versus risk exposure.

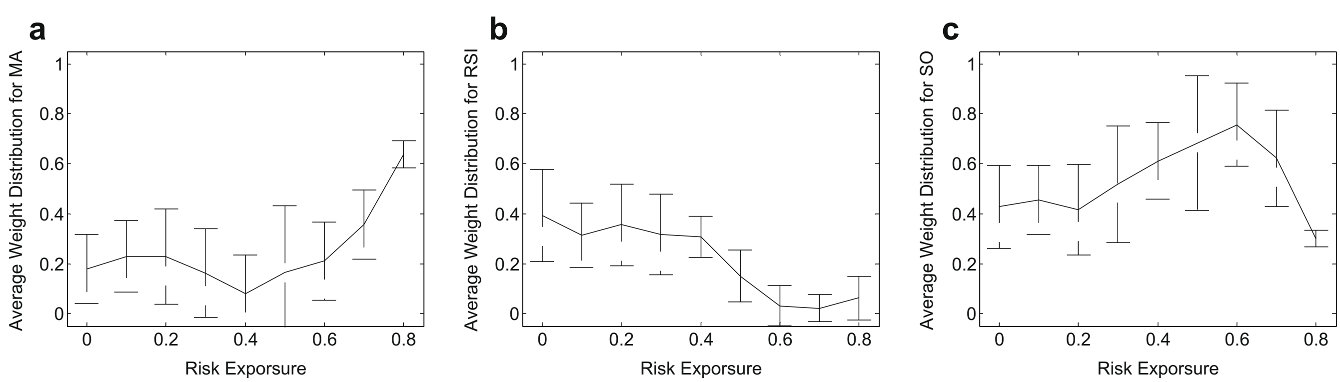

Fig. 18. Statistical distribution of the average weight for (a) MA, (b) RSI and (c) SO at discrete values of risk exposure of 0.1. The vertical lines denote the standard deviation of the weight at each value of risk exposure.

further partitioned into two independent set i.e. training and test set. During the evolutionary process, the fitness of the trading agents will be assessed based on the training set. The final solutions obtained at the terminal generation will be subsequently applied to the test set to evaluate its generalization performance, indicating its real efficiency in unseen data. The total returns and risk exposure in the training and test data will be conveniently referred as training returns, training risk, test returns and test risk respectively in the rest of the paper.

The risk-returns tradeoff for the training and test data in one of the experimental run is illustrated in Fig. 19. As the TTS are evolved with respect to the training data, the risk-returns tradeoff is clearly evident in Fig. 19a. However, such relationship is not evident when the same set of TTS is applied to the test data. While returns of 60% are achievable at a risk level of 0.2 in the training data, losses are incurred at the same level of risk in the test data. Clearly, positive returns in the training data do not necessarily correspond to positive returns in the test data. In fact, the low correlation between training and test returns was also briefly suggested by Korczak and Lipinski (2004) before, where they observed that applying a fitness measure strongly based on returns usually result in inefficiencies in test data. As such, they even suggested that profits should be restricted to post training assessment. Nevertheless, most single-objective approaches for ETTS are still based on the underlying assumption of the positive correlation between training and test returns.

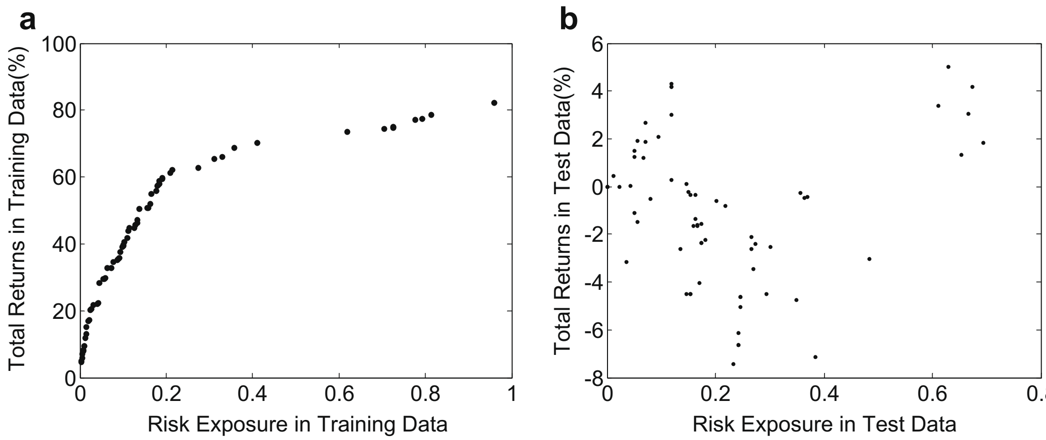

Fig. 19. Pareto fronts obtained for (a) training data and (b) test data.

Thus, before examining the generalization performance of the ETTS in proper, it is important to understand further the correlation between the performance in the training data and test data. Specifically, this refers to the correlation analysis of the following four variables: training returns, training risk, test returns and test risk.

Based on the ETTS found in 10 experimental runs, the correlations between the various variables are plotted in Fig. 20. Several interesting insights are revealed in these plots. The plot of training returns and training risk illustrates accurately the risk-returns tradeoff, while a noisy version can be observed in the plot of test returns and test risk, despite the low correlation between training returns and test returns.

Contrary to the assumption in single-objective optimization approach where higher training returns is associated with higher test returns, this relationship is sorely missing from these plots. Instead, higher training returns are associated with increased volatility in the expected test returns as reflected by the widening spread of the solutions. This is illustrated clearer in Fig. 21, which plots the mean and the standard deviation (denoted by the vertical lines) of the test returns at intervals of 10 for the training returns. While the mean test returns does not increase much for larger values of training returns, there is a general increase in the standard deviation instead.

Noticeably, there is a positive correlation between the training risk and test risk instead, though it is slightly skewed towards the former, as the fitness function is based on the training data. Nonetheless, this positive correlation is rather intuitive. An active TTS will generally generate buy and sell signals at higher frequency within a trading period. Thus, it is most probable that such a TTS will consistently generate active schedule for both the training data and test data.

These observations seem to suggest that training and test returns are related indirectly via risk instead of the direct relationship that is widely assumed in single-objective approaches. Specifically, a TTS that yields high training returns is most likely to be associated with higher training risk by virtue of the risk-returns tradeoff. Due to the positive correlation between the training risk and test risk, this TTS will most likely trade actively in the test data. Consequently, since it is not optimized to the test data, this results in test returns of high volatility. The noisy version of the risk-return frontier in the plot of test returns and test risk could be attributed to these factors. Of course, these assertions are merely hypothetical and should be further verified by experimental studies. Nevertheless, it does show that positive correlation between training returns and test returns assumed in conventional single-objective approaches of ETTS optimization does not necessarily hold for all cases.

4.3. Generalization performance

To formally evaluate the generalization performance of the ETTS found by the proposed MOEA, a total of ten different set of experimental data is used to compensate the high dependence of generalization performance on the choice of the trading period. Each experimental set comprised of one full year of test data, starting from the first trading day of January to the last trading day of December from the year 1995 to 2005, while the previous three years of trading data were used as the training set as shown in Table 5. About 100 days of historical data prior to the first trading day of the training set were included also.

Performance evaluation is not as straightforward in multi-objective approach as compared to single-objective approach. For the latter, the sole solution obtained at the end of the evolutionary process will be used to quantify the overall generalization performance. However, as a set of solutions will be obtained instead in multi-objective optimization, this led to the selection problem of choosing the appropriate solutions for the evaluation of its generalization performance. An easy approach is to simply consider the average performance of the various ETTS obtained but this does not account for their varying degree of risk averseness.

Instead, ETTS obtained from the training set is classified according to the training risk in regular interval of 0.1 due to the positive correlation between training and test risk measure. They are then applied to the test data and the average returns in each group are calculated, as listed in Table 6. The returns for the buy-and-hold strategy are included also as a basis for comparison. It should be highlighted that the returns of the buy-and-hold strategy are extremely volatile, depending entirely on the trading period i.e. high returns could be reaped during bull markets where investor confidence is high, leading to widespread financial asset appreciation, and vice versa for bear markets.

On the other hand, the returns for ETTS are much more conservative. In period where the buy-and-hold strategy can yield a profit of 76.60%, it can only achieve a maximum of 20.18% at a risk level of 0.3. And when the market dropped by 31.72% in 1997, the ETTS are able to generate positive returns for all risk level. These conservative results could be partly due to the averaging of solutions within the risk intervals.

Considering the arithmetic sum of the returns generated by the ETTS at the various risk level, its test returns can only outperform the buy-and-hold strategy at one particular risk level. However, it

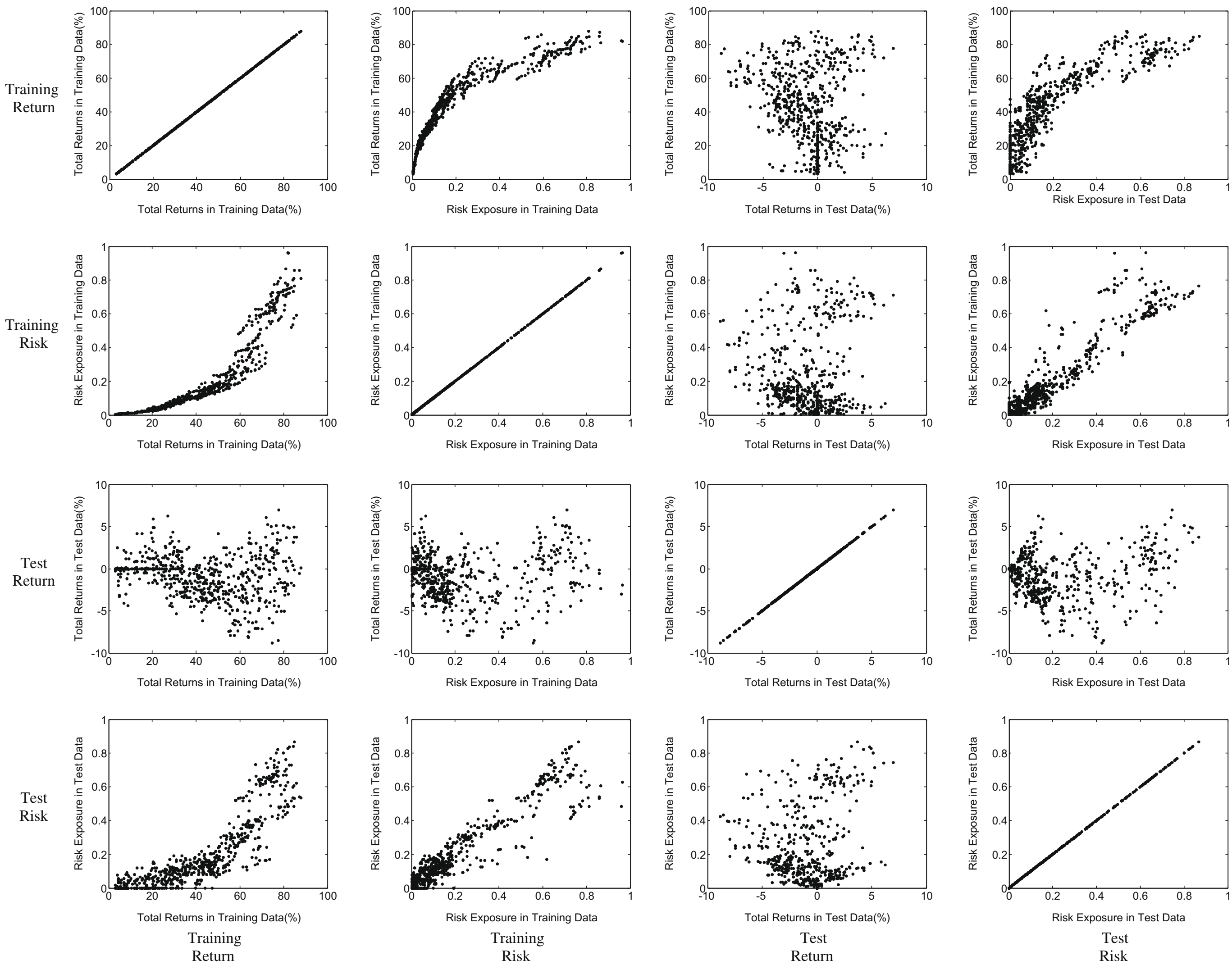

Fig. 20. Correlation between training returns, training risk, test returns and test risk.

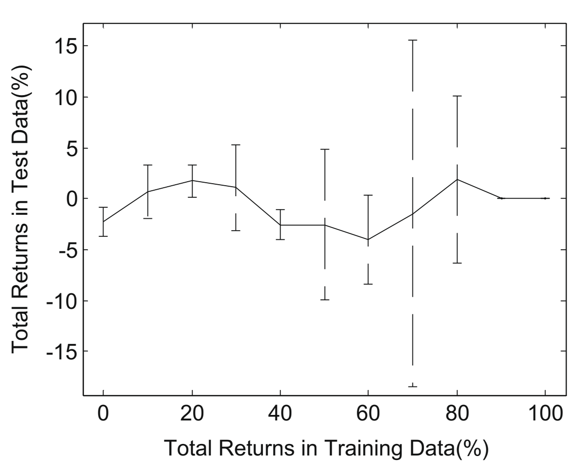

Fig. 21. Statistical distribution of the average test returns at discrete values of training return of 10. The vertical lines denote the standard deviation of the weight at each value of risk exposure.

should be highlighted that the returns of the buy-and-hold strategy is attained at the maximum risk level as this strategy remain in the open position for 100% of the trading period.

To reinforce the claims in the previous section, Fig. 22 plots the mean and variance of the test returns versus training risk for the various experimental sets. In Fig. 22a, the mean of the test returns fluctuates around the zero mark as training risk increases. Positive returns could hence be obtained if the transaction cost of 0.5% is not considered. This result is consistent to that obtained by Allen and Karjalainen (1999) where their evolved rules did not generate excess returns over buy-and-hold strategy after the inclusion of transaction costs. The steady increase in the variation of the test

Table 5
Generalization performance of MOEA over 10 different set of experimental data.

Index	Training set		Test set	
	Start	End	Start	End
96	04-031-993	29-12-1995	02-01-1996	31-12-1996
97	03-011-994	31-12-1996	03-01-1997	31-12-1997
98	03-011-995	31-12-1997	02-01-1998	31-12-1998
99	02-011-996	31-12-1998	04-01-1999	30-12-1999
00	03-011-997	30-12-1999	03-01-2000	29-12-2000
01	02-011-998	29-12-2000	02-01-2001	31-12-2001
02	04-011-999	31-12-2001	02-01-2002	31-12-2002
03	03-012-000	31-12-2002	02-01-2003	31-12-2003
04	02-012-001	31-12-2003	02-01-2004	31-12-2004
05	02-012-002	31-12-2004	03-01-2005	30-12-2005

Table 6
Generalization performance of MOEA over 10 different set of test data.

Index	Buy-and-hold returns	MOEA returns										
Risk level												
		0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
96	−2.33	0.16	−4.77	−7.48	11.52	6.52	8.09	0.00	0.00	0.00	0.00	0.00
97	−31.72	0.28	4.02	1.85	0.00	5.17	9.41	13.92	0.00	0.00	0.00	0.00
98	−8.76	0.38	16.75	−1.90	9.82	0.00	0.00	−27.18	0.00	0.00	0.00	0.00
99	76.60	−4.34	−2.18	−0.06	20.18	−7.76	0.00	0.00	12.35	9.15	0.00	0.00
00	−25.90	1.07	7.89	−0.67	5.11	9.28	−15.12	−8.30	−3.83	−5.57	0.00	0.00
01	−14.88	−6.79	−6.89	−12.45	−10.28	−0.07	0.00	0.31	−7.91	−8.81	0.00	0.00
02	−18.01	0.49	−0.24	−1.76	−4.16	−5.79	0.00	−22.58	−18.74	0.00	0.00	0.00
03	31.58	0.60	3.17	9.48	4.85	1.82	−7.06	−3.75	0.00	0.00	0.00	0.00
04	14.384	0.04	0.44	−0.61	1.53	0.92	0.96	−1.26	0.00	2.08	−2.85	0.00
05	12.89	0.04	−1.58	−4.08	−0.92	−3.79	−1.08	4.35	0.00	0.06	0.00	0.00
Arithmetic sum	34.31	−8.06	16.61	−17.69	37.64	6.31	−4.79	−44.48	−18.12	−3.09	−2.85	0.00

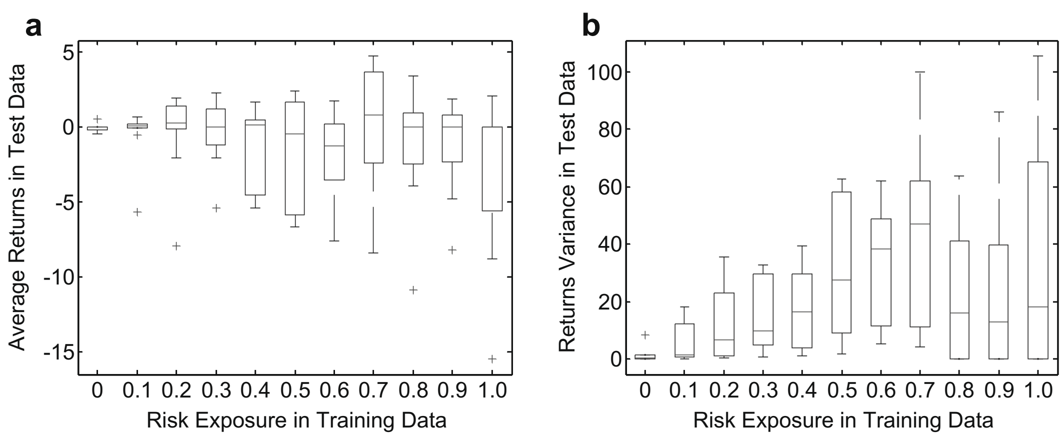

Fig. 22. (a) Mean and (b) variance of the test returns for experiment sets.

returns in Fig. 22b further verified the hypothesis that higher training returns correspond to increased volatility in the test returns. The drop after risk level of 0.8 is statistically insignificant due to the lack of solutions in that region.

Ideally, the multi-objective evolutionary platform could evolve a set of TTS with different level of risk averseness so as to suit the different types of investors, from conservative to risky. However, the erratic behaviors in the generalization performance, caused by the low correlation between the training returns and test returns, complicate the task of choosing the appropriate ETTS for practical implementation. Nevertheless, the experimental result does reveal some interesting insights to this problem, in particularly, the observation that the positive correlation between training returns and test returns assumed in conventional single-objective approaches of ETTS optimization does not necessarily hold for all cases.

5. Conclusions

In this paper, a multi-objective evolutionary approach to the development of TTS was investigated, where total returns and risk exposure were simultaneously optimized. Popular technical indicators used commonly in real-world practices were used as the building blocks for the trading agents, allowing the examination of their trading characteristics under an evolutionary platform. The Pareto front obtained by the algorithm accurately depicts the inherent tradeoff between risk and returns. The analysis of the TI composition along the risk-return frontier reveals that each TI has varying degrees of significance in different regions of the trade-off surface depending on their underlying characteristic. As such, future work will certainly involve profiling other TI to further understand their trading characteristics.

The correlation study suggested that the returns from the test and training data are not correlated in this context, which is contrary to popular belief in the single-objective approach of this optimization problem. Instead, higher returns in training data only corresponds to larger volatility in the returns generated in the test data. This is further reinforced by the erratic trends in the analysis of the generalization performance. Nevertheless, in order to further validate the evolutionary model and the empirical results, it is absolutely necessary to subject the evolutionary model to other experimental data and include different TI that are able to detect other market signal not covered by the current group of TI.

References

Alexander, S. S. (1961). Price Movements in speculative markets: Trends or random walks. *Industrial Management Review, 2*(2), 7–26.

Allen, F., & Karjalainen, R. (1995). Using genetic algorithms to find technical trading rules. *Working paper*. The Wharton School, University of Pennsylvania.

Allen, F., & Karjalainen, R. (1999). Using genetic algorithms to find technical trading rules. *Journal of Financial Economics, 51*(2), 245–271.

Becker, L., & Seshadri, M. (2003). GP-evolved technical trading rules can outperform buy and hold. In *Proceedings of the sixth international conference on computational intelligence and natural computing*.

Bernstein, P. L., & Damodaran, A. (1998). *Investment management*. John Wiley & Sons.

Bosman, P., & Thierens, D. (2003). The balance between proximity and diversity in multi-objective evolutionary algorithms. *IEEE Transaction on Evolutionary Computation, 7*(2), 174–188.

Branke, J. (1999). Evolutionary approaches to dynamic environments: A survey. In *GECCO workshop on evolutionary algorithms for dynamic optimization problems* (pp. 134–137).

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance, 47*(5), 1731–1764.
Brown, S. J., Goetzmann, W. N., & Kumar, A. (1998). The Dow theory: William Peter Hamilton's track record reconsidered. *Journal of Finance, 53*(4), 1311–1333.
Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The econometrics of financial markets*. Princeton, NJ: Princeton University Press.
Chen, S. H., & Yeh, C. H. (1997). Toward a computable approach to the efficient market hypothesis: An application of genetic programming. *Journal of Economic Dynamics and Control, 21*(6), 1043–1063.
Cheong, C. Y., Tan, K. C., & Veeravalli, B. (2007). Solving the exam timetabling problem via a multi-objective evolutionary algorithm: A more general approach. In *IEEE symposium on computational intelligence in scheduling 2007* (April 1–5, pp. 165–172). Honolulu, HI, USA.
Colby, R. W., & Meyers, T. A. (1988). *The encyclopedia of technical market indicators*. Dow Jones-Irwin.
Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms*. New York: John Wiley & Sons.
Dowd, K. (2000). Adjusting for risk: An improved Sharpe ratio. *International Review of Economics and Finance, 9*(3), 209–222.
Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 23*, 383–417.
Fama, E. F., & Blume, M. E. (1966). Filter rules and stock-market trading. *Journal of Business, 39*(1), 226–241.
Fyfe, C., Marney, J. P., & Tarbert, H. F. E. (1999). Technical analysis versus market efficiency: A genetic programming approach. *Applied Financial Economics, 9*(2), 183–191.
Garcia-Almanza, A. L., & Tsang, E. P. K. (2006). Simplifying decision trees learned by genetic algorithms. In *Proceedings of the congress on evolutionary computation* (pp. 7906–7912).
Iba, H., & Nikolaev, N. (2000). Financial data prediction by means of genetic programming. In *Proceedings of the 6th international conference on computing in economics and finance*.
Jangmin, O., Lee, J., Lee, J. W., & Zhang, B. T. (2005). Dynamic asset allocation for stock trading optimized by evolutionary computation. *IEICE Transactions on Information and Systems, 88*, 1217–1223.
Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance, 45*(3), 881–898.
Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance, 48*(1), 65–91.
Jensen, M. C. (1968). Problems in selection of security portfolios: The performance of mutual funds in the period 1945–64. *Journal of Finance, 6*.
Jiang, R., & Szeto, K. Y. (2003). Extraction of investment strategies based on moving averages: A genetic algorithm approach. In *Proceedings of the 2003 IEEE international conference on computational intelligence for financial engineering* (pp. 403–410).
Kendall, G., & Su, Y. (2003). A multi-agent based simulated stock market – Testing on different types of stocks. In *Proceedings of the 2003 congress on evolutionary computation* (Vol. 4, pp. 2298–2305).
Kho, B. C. (1996). Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets. *Journal of Financial Economics, 41*(2), 249–290.
Korczak, J., & Lipinski, P. (2004). Evolutionary building of stock trading experts in a real-time system. In *Proceedings of the 2004 congress on evolutionary computation* (pp. 940–947).
Korczak, J., & Roger, P. (2002). Stock timing using genetic algorithms. *Applied Stochastic Models in Business and Industry, 18*(2), 121–134.
Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics, 105*(1), 1–28.
Li, J., & Tsang, E. P. K. (1999). Improving technical analysis predictions: An application of genetic programming. In *Proceedings of the twelfth international Florida artificial intelligence research society conference* (pp. 108–112).
Lim, M., & Coggins, R. J. (2005). Optimal trade execution: An evolutionary approach. In *Proceedings of the 2005 IEEE congress on evolutionary computation* (Vol. 2, pp. 1045–1052).
Lin, L., Cao, L., Wang, J., & Zhang, C. (2004). The applications of genetic algorithms in stock market data mining optimisation. In *Proceedings of 5th international conference on data mining, text mining and their business applications* (pp. 273–280).
Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction? *Review of Financial Studies, 3*(2), 172–205.
Lui, Y. H., & Mole, D. (1998). The use of fundamental and technical analyses by foreign exchange dealers: Hong Kong evidence. *Journal of International Money and Finance, 17*(3), 535–545.
Lukac, L. P., Brorsen, B. W., & Irwin, S. H. (1988). A test of futures market disequilibrium using twelve different technical trading systems. *Applied Economics, 20*(5), 623–639.
Mahfoud, S., & Mani, G. (1996). Financial forecasting using genetic algorithms. *Applied Artificial Intelligence, 10*(6), 543–566.
Murphy, J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. Prentice-Hall.
Neely, C. (2003). Risk-adjusted, ex ante, optimal technical trading rules in equity markets. *International Review of Economics and Finance, 12*(1), 69–87.
Neely, C., Weller, P., & Dittmar, R. (1997). Is technical analysis in the foreign exchange market profitable? A genetic programming approach. *Journal of Financial and Quantitative Analysis, 32*(4), 405–426.
Ready, M. J. (2002). Profits from technical trading rules. *Financial Management, 31*(3), 43–61.
Schoreels, C., & Garibaldi, J. M. (2005). A comparison of adaptive and static agents in equity market trading. In *Proceedings of the IEEE/WIC/ACM international conference on intelligent agent technology* (pp. 393–399).
Schoreels, C., Logan, B., & Garibaldi, J. M. (2004). Agent based genetic algorithm employing financial technical analysis for making trading decisions using historical equity market data. In *Proceedings of the IEEE/WIC/ACM international conference on intelligent agent technology* (pp. 421–424).
Sharpe, W. F. (1966). Mutual fund performance. *Journal of Business, 39*(1), 119–138.
Tan, K. C., Cheong, C. Y., & Goh, C. K. (2007). Solving multi-objective vehicle routing problem with stochastic demand via evolutionary computation. *European Journal of Operational Research, 177*, 813–839.
Tan, K. C., Chew, Y. H., & Lee, L. H. (2006). A hybrid multi-objective evolutionary algorithm for solving vehicle routing problem with time windows. *Computational Optimization and Applications, 34*, 115–151.
Tan, T. Z., Quek, C., & Ng, G. S. (2005). Brain-inspired genetic complementary learning for stock market prediction. In *Proceedings of the 2005 IEEE congress on evolutionary computation* (Vol. 3, pp. 2653–2660).
Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance, 11*(3), 304–314.
Wang, J. H., & Chen, S. M. (1998). Evolutionary stock trading decision support system using sliding window. In *Proceedings of the 1998 IEEE international conference on computational intelligence* (pp. 253–258).
Weissman, R. L. (2005). *Mechanical trading systems: Pairing trader psychology with technical analysis*. Wiley Trading.
Werner, F. M., Bondt, D., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance, 42*(3), 557–581.
Zitzler, E., Deb, K., & Thiele, L. (2000). Comparison of multi-objective evolutionary algorithms: Empirical results. *Evolutionary Computation, 8*(2), 173–195.
Zitzler, E., & Thiele, L. (1999). Multi-objective evolutionary algorithms: A comparative case study and the strength Pareto approach. *IEEE Transactions on Evolutionary Computation, 3*(4), 257–271.
Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., & Fonseca, V. G. (2003). Performance assessment of multi-objective optimizers: An analysis and review. *IEEE Transactions on Evolutionary Computation, 7*(2), 117–132.