Directive Decision Devices: Extending the reach of automation into the finance domain

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A B S T R A C T
Expert systems, decision support systems, and knowledge management systems are computer constructs that are designed to service human decision makers. There are however certain sorts of decision situations where, for some reason, responsibility might better be invested in a computer program, rather than a person. This paper points out several such situations that can be found in the contemporary financial management sector, and suggests how Directive Decision Devices might be equipped to deal with them on a stand-alone basis.

1. Introduction

It is important that firms investing in IT-enabled systems determine whether the selected system, and its capabilities, support the corporate strategy, and more importantly, the business strategy for which the system is developed or proposed (see Baets, 1992; Bakos and Treasy, 1986; Mukherji, 2002; Pyburn, 1983). Certain systems are designed to give complete autonomy to computer systems – while others allow human–machine symbiosis. For instance, Airbus and Boeing employ different strategies in the envelope protection in fly-by-wire control systems. A fly-by-wire control system is more beneficial than its conventional counterpart. Airbus employs a hard limit protection strategy whereby the fly-by-wire system can take control of the aircraft from the pilot at a pre-defined threshold. This is probably in recognition of the fact that in crises, the timeliness of a response may be determined with reference to a fixed instant in the form of an absolute action threshold. This establishes the last possible point in time where any sort of conceivable solution is available. Once an action threshold is passed, a crisis is no longer containable; whatever adverse consequences a problem portends, are thereafter inescapable. For instance, if an airplane is flying towards a building, with hard limit protection the Airbus airplane’s fly-by-wire control system will avoid a collision by automatically shifting the plane’s flight path away from the building to escape a tragedy.

On the other hand, Boeing’s strategy is that “…the pilot in control of the aircraft should have the ultimate authority” (Wallace, 2000). With this strategy, the system only informs the pilot about possible dangers as the plane seems to approach protected boundaries. Perhaps the greatest benefit from this strategy is that the pilot has the capability to make decisions in situations that were not considered, or unforeseen by the system designers. In such circumstances, the Airbus strategy of complete autonomy by the computer systems could lead to a catastrophe where both a human and a machine are unable to make the effective decision because of the novelty of the problem, and the inability of the pilot to act.

The envelope protection problem and its related solutions are also applicable to other problems in various applications and business settings. In the financial industry for instance, there are situations where a system is needed to help the decision maker make an effective decision. There are other cases where it may be appropriate for the machine to make a decision autonomously.

Organizations have made tremendous investments in diverse IT systems, including decision support systems (DSS), expert systems, and knowledge systems. Specific to finance, these expenditures support activities such as portfolio selection and optimization, investment marketing, investment advisory, financial analysis, and banking management (Matsatsinis,Doumpos, and Zopounidis,1997).

Despite the great promise of these varied IT-enabled systems, there is concern over the risk that they pose in terms of how decision makers can make fraudulent deals using these systems. A case in point is where Joseph Jett, ex-bond trader for Kidder Peabody & Company, committed securities fraud when he allegedly created $350 million in “phantom” profits to enjoy a $9 million bonus

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A similar case involves the deceptive activity of Sal-

Then the bull market turned bearish, Grub-

executory, compensatory, interdictive, and
coptive. We present a summarized description
of these devices and detail the application of these constructs to financi-
sional situations.

The balance of human–machine variations, in terms of whether a
system should be only controlled by a machine, or support a human
decision maker, is critical (Kasper and Andoh-Baidoo, 2006). How-
ever, investigation of the literature has not revealed any research
that discusses this human–machine problem. Most research on
DSS, knowledge management systems, and expert systems, focus on
how these systems assist humans in decision-making (Matsat-
sinis et al., 1997; Wang, Mylopoulos, and Liao, 2002). In this paper,
we apply a specific class of computer-centered constructs, called
Directive Decision Devices, as introduced by Sutherland (2008) to
the financial domain. These devices can be configured to function
as automated decision makers. There are four broad categories of
Directive Decision Devices based on the task that they are commis-
sioned to perform. These categories are: executory, compensatory,
interdictive, and cooptive. We present a summarized description
of these devices and detail the application of these constructs to financi-
sional situations.

The rest of the paper is organized as follows: first presented is
the distinction between Directive Decision Devices and DSS. Then
the four types of Directive Decision Devices are presented. For each
class, financial domains are suggested where the Directive Decision
Device could be useful. This is followed with a discussion of the
reach of Directive Decision Devices by explicating prototypical
constructs and the characteristics of those constructs. While Direc-
tive Decision Devices have tremendous potential in finance, there
are boundaries. Therefore, we discuss the limitations of Directive
Decision Devices. Lastly, we conclude by suggesting future re-
search possibilities for Directive Decision Devices.

### 2. Decision support systems

Directive Decision Devices are differentiated from traditional
DSS in that DSS have merely an advisory mission of volitional
employment. However, Directive Decision Devices are commis-
sioned by organizational superiors, and subsequently imposed on
subordinates. We also distinguish conventional DSS from Directive
Decision Devices in that, where the former performs at the com-
mandment of the individual, the latter places the individual in ser-
vice to the machine.

DSS have been described in several ways. Power (2000) charac-
terizes DSS as computer based systems that assist decision makers
(managers) using models and data, and additionally identify and solve
problems. These problems are categorized as unprogrammed,
unstructured (or semi-structured). DSS must be interactive, easy to
use and assist decision makers manipulate and use data. Bonczek,
Holsapple, and Whinston (1981) argue that managers must be al-
lowed to apply heuristics, checklists, and build and use mathematic-
ical models. Turban (1990) indicates that DSS have four main charac-
teristics: (1) incorporate models and data, (2) assist manag-
ers in making semi-structure or unstructured decisions, (3) sup-
port (not replace) managerial judgment, and (4) improve decisions’ effectiveness, not the efficiency of making the decision.

DSS are employed in several finance domains to support deci-

d-locations. An example is a web based integrated framework
for portfolio selection (Dong, Du, Wang, Chen, and Deng, 2004).
Other intelligent-based systems have also been employed in sev-

eral financial applications including contract processes (Lee and
Lee, 1998) and investment management (Dudge and Keynes, 1996).

### 3. Directive Decision Devices categories

At a minimum, Directive Decision Devices may just function as
set of instructions running on a computer and acting in conjunc-
tion with a company’s separate data gathering and decision imple-
mentation apparatus. At the most sophisticated level, Directive
Decision Devices can be a combination of several computer pro-
grams and hardware and have the ability to not only gather data
for input and determine the decision, but also enact the choice – all
absent of human intervention.

Using Sutherland’s (2008) definition of taskings as the basis for
our categories, we present in Table 1, a description and financial
application for each Directive Decision Device Type. As stated,
the four Directive Decision Device categories are: executory, com-

pensatory, interdictive, and cooptive. Regardless of which category
a Directive Decision Device is resident, and regardless of whether
a Directive Decision Device acts autonomously, or as the lead
member of a Human-Directive Decision Device pairing, all must

<table>
<thead>
<tr>
<th>Direct Decision Device category</th>
<th>Responsibility</th>
<th>Charge</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Executory</td>
<td>Entirely replaces decision-maker authority over a specific type or class of decisions</td>
<td>Commissioned as a stand-alone entity. Executes completely independent of human presence</td>
<td>Automated mortgage approvals</td>
</tr>
<tr>
<td>Compensatory</td>
<td>Compensates for human functional deficiencies</td>
<td>Acts as a mandatory systems for users</td>
<td>Cash register pictures of food items at a fast food chain</td>
</tr>
<tr>
<td>Interdictive</td>
<td>Prohibits (Interdicts) human action under certain pre-defined situations</td>
<td>Usually transparent to those that use them. Stops further action until corroborated</td>
<td>Prevention of Credit Card Fraud – Blocks usage of card if pattern of use is abnormal</td>
</tr>
<tr>
<td>Cooptive</td>
<td>Takes control of a situation if a human functionary fails to act in a certain pre-determined time</td>
<td>The systems adopts (Coopts) the responsibility and take action autonomously</td>
<td>Halts trading of stocks automatically if price change in specific time period is exceeded</td>
</tr>
</tbody>
</table>
have the following characteristics: (1) a way of acquiring and massaging decision predicates; (2) something in the way of embedded instrument(s) to effect the election of decision choices or, more generally, to support response-selection; and (3) some way of arranging for the implementation (enactment) of the decision choices at which they have arrived (or provide such function itself).

3.1. Executory

Executory constructs are true and complete decision agents. They are designed to execute a decision function entirely without any human intervention or contribution. Included in the domain of decision functions for which a computer program is sufficient would be those where a decision choice is to be determined by taking recourse to a decision table or something similar. Also included would be those systems where a neat algorithmic resolution is both available and appropriate. More generally, this means decision situations where neither discretion, nor contextual sensibilities are required or desired.

3.2. Compensatory

Compensatory systems are targeted at areas where: (a) the likelihood of a proper (rational, if not optimal) choice is dependent on the technical skills or sensibilities of the decision-making agent, and (b) there is some reason to suspect – or alternatively, no reason to expect, that a human functionary will be adequately equipped with such skills or sensibilities. Thus, administrative functions, requiring quantitative analysis capabilities, are among the most obvious candidates for transfer to a compensatory program.

3.3. Interdictive

Interdictive devices have a preventative mission. When an interdictive program is in place, local management decisions or directives would not actually be implemented unless they have been corroborated by the computer as innocent of any predictably parlous prospects or procedural improprieties. Interdictive constructs are then a means for intercepting prospective endogenous threats. They would prevent a system’s computers from executing an operator-ordered initiative until it has been validated (i.e., corroborated) as innocent of any predictably perilous consequences. Ideally, they will be invisible to those on whom they are intended to watch.

3.4. Cooptive

Cooptive devices would be designed to seize the initiative and implement an appropriate course of action (contingency planning script) if the human manager has not already done so prior to some point in time. Cooptive constructs may make their most crucial contribution in situations where a human decision-maker might naturally be expected to be reluctant to act. That is, coptive constructs are well suited to cover true quandaries, i.e., situations where, reminiscent of “Hobson’s choice,” all available alternatives are equally unattractive. The Airbus system for envelope protection is an example of a cooptive system.

4. Prototypical constructs

4.1. Directive Decision Devices reach

Directive Decision Devices are only applicable to technically tractable decision situations. Therefore, these devices are either programmatic or algorithmic. As depicted in Table 2 these situations must fall into one of four families in order to be solvable by a Directive Decision Device. The Categorical/Deterministic family houses those facilities that are simple rule-based structures, likened to decision tables and elementary decision trees (Quinlan, 1990; Singh, Salam, and Iyer, 2003). The facility’s family of computational/deterministic takes care of those problems that can be solved via ordinary-mathematical optimization and analysis methods. Situations requiring facilities that are probabilistic can fit into categories that are comprehensive predictive constructs, presented to the device as a classification or regression tree. Lastly, the probabilistic/computational family houses extrapolative-projective techniques, which are normally statistical inference type problems.

4.2. Prototypical types

As discussed, Directive Decision Devices are categorized as executory, compensatory, interdictive, or coptive, and possess the ability to direct the decisions of their users. While these devices all have functions (tasks that detail what the Directive Decision Device can do), and facilities (instruments that either direct or carry the means of completing the assignment), each has differing levels of sophistication (capabilities).

Fig. 1 is an adaptation of Prototypical Directive Decision Devices (Sutherland, 2008). In this section, we describe the functionality of the super-categories, which progress from least to most capable as follows: elementary (automata-type), compound (manifold) network constructs, and full-featured (process control constructs).

4.2.1. Elementary (automata-type)

Elementary capability-ordered prototypical devices are minimally functional. These types, only at most, offer the minimal tasks of data acceptance, problem recognition, and appropriate decision determination. This leaves such activities as the triggering mechanism, the supply of actual decision predicates, and the activation of its decision choice, to exogenous agents.

It follows that with the increase in the sophistication of the instrumentation resident in Types 3 and 4 automata-type devices, versus those in Types 1 and 2 devices, the former relatively offer more functions. The increase in functionality results in the ability to perform more competently and completely. Types 1 and 2 devices contain deterministic instrumentation while their counterparts are probabilistically instrumented, which makes the former devices offer only simple associative inferences (rote learning or classical conditioning), while the latter has the capability to perform inductive inference operations (going from the particular to the more general).

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Families of instrumental facilities (adapted from Sutherland (2008)).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Categorical and deterministic</td>
<td>Rule based – decision tables and decision trees</td>
</tr>
<tr>
<td>Categorical and probabilistic</td>
<td>Predictive – regression and classification trees</td>
</tr>
<tr>
<td>Computational and deterministic</td>
<td>Algorithmic – numerical analysis and mathematical optimization</td>
</tr>
<tr>
<td>Computational and probabilistic</td>
<td>Extrapolative (projective) – statistical inference</td>
</tr>
</tbody>
</table>

Fig. 1 is an adaptation of Prototypical Directive Decision Devices (Sutherland, 2008). In this section, we describe the functionality of the super-categories, which progress from least to most capable as follows: elementary (automata-type), compound (manifold) network constructs, and full-featured (process control constructs). Appendix A presents taxonomy of the characteristics of each of the prototypical types of the Directive Decision Device constructs to allow for an easy identification of the characteristics of each “type” as defined in Fig. 1.
Regression trees can represent multivariate regression functions where the independent variables are often continuous and the dependent variable(s) are cardinal or numerical.

4.2.2. Compound (manifold) network constructs

Types 5 and 6 have the commonality of having hybrid node-arc constructs that link categorical (qualitative) and computational (quantitative) analytical facilities. While tree constructs found in Type 4 devices hold externally determined values, the composite constructs’ nodes contain algorithmic expressions. Therefore, the arc that protrudes from the node can be made dependent of values assigned the transit variables by the local nodal algorithm. Since the nodes can house differing computational forms, they have the unique capability of being able to encode and execute compound (multi-stage, manifold) decision-making or problem-solving (resulting in the super-category’s descriptive term “manifold”). This enables these types of Directive Decision Devices to act more “managerial” (multiple decisions) versus enacting simple/single decisions.

As managerial agents, Types 5 and 6 are the first to have endogenous data acquisition facilities. In addition, these devices will be the first on the continuum to have internal enactment capabilities. The differences between Types 5 and 6 are their target applications. Type 5, as a deterministic recursive model, allows for one-directional causality and hierarchical impacts. Type 6, as a stochastic node-arc construct, allows for multi-directional causality. Since neural networks are stochastic, and offer unmanaged and undirected pattern-recognition, they can be categorized as Type 6. While initially Type 6 devices may take certain patterns as input, over time, they will improve their patterns without additional exogenous inputs.

4.2.3. Full-featured (process control constructs)

Types 7 and 8 act similarly to process control systems. (Leveson, Heimdahl, Hildreth, and Reese, 1994). As the most sophisticated of the prototypical constructs, they not only have the capability of data acquisition and enactment, but they also take control and bring the system within allowable limits. This may be an increase or decrease, as necessary. While both Types 7 and 8 are process control systems that attempt to keep a system in a desired state, they do so differently. Type 7 devices make corrections to the system in a direction opposite to the deviation. They are similar to conventional first-order control systems. Corrections are made after-the-fact, using deterministic rectification algorithms.

Type 8 devices offer an anticipatory function and control moderately stochastic processes. Using an array of projective values for process variables, Type 8 devices are enacted as necessary. These devices are analogous to second-order control systems. (see Leveson et al., 1994). Not only can these devices move in a certain direction, but they also have the capability of accelerating or decelerating the projective functions for the process variables of interest. Because they have second-order qualities, Type 8 devices are generally chosen to control rate variables. Additionally, Type 8 devices have the distinct characteristic of changing the algorithms that cause the change by comparing the actual to the expected state. These adaptive capabilities allow their comparison to higher-end cybernetic-inspired process management constructs.

4.3. Directive Decision Devices limitations

As stated, Directive Decision Devices are only capable of making technically tractable decisions. Thus, unless the designers of the device instrumented the system to analytically (algorithmic or programmatic/scripted) determine the decision, the device cannot do so. This then eliminates those decisions that are obtained interactively or collaboratively. When the characteristics of subjects cannot be captured by an orthodox quantitative expressions or set of such (like a set of a solvable system of equations), a Directive Decision Device is of no assistance. Excluded also are entire species of decisions for which objectively predicated, unambiguously actionable qualitative conclusions are beyond reach (e.g., strategic (intelligence-driven), rationalistic (judgment-driven), axiomatic (precept-driven) and axiological (value-driven)).

As mentioned, probabilistic tree-type constructs have been purported to provide inductive inference capabilities (Auriol, Wess, Manago, Althoff, and Traphöner, 1995; Quinlan, 1986). What is most often the case is that the system performs statistical inference operations (just a computational form of induction). Thus, only a subset of the entire domain of inductive logic is covered. This operation generalizes the results from density or frequency distributions. Therefore, more sophisticated generalizations such
as Galilean, Darwinian, and Newtonian are not obtainable using Directive Decision Devices.

5. Financial applications of Directive Decision Devices

Now, we examine business processes of some typical domains in finance and suggest how Directive Decision Devices have been, and can be used, to support these processes.

Table 3 is a 4 × 3 “categories versus prototypical construct” matrix of relevant business functions where Directive Decision Devices are appropriately applied in the financial industry.

5.1. Executory examples

Financial functions where elementary level executory type Directive Decision Devices are appropriate include credit granting, mortgage lending, credit reporting, insurance granting, and program trading. Some commercial banks have displaced the responsibility for credit granting and mortgage lending decisions from local branch managers to corporate computers. This is in pursuit of their corporate strategy to achieve consistency and objectivity in this domain. The processes involved in credit granting and mortgage lending may not always involve human intervention. In situations where businesses do not want to introduce subjectivity from the decision maker, the use of a Directive Decision Device would be appropriate.

The conversion of lending decisions could be, and is being, effectively used particularly by those firms where subjectively predicated lending decisions led to charges of discriminatory lending, known as “redlining”. A Directive Decision Device would make the decision that would occur absent of any subjective influence from the decision maker’s idiosyncrasies. Typically, lenders can be classified based on objective parameters such as annual income and credit score. Thus, the Directive Decision Device’s decision can be monitored to ensure that objective and consistent decisions are made by the automated machine.

Existing program trading protocols are also examples of executory elementary type Directive Decision Devices. Typically, institutional investors use these protocols to execute large volume trades automatically without human intervention.

Given parameters, such as the risk-return value, the ratio of the components of the assets, and a list of acceptable or unacceptable stocks specified by an investor, a computer program could effectively maximize an individual investor’s portfolio without the subjective analysis of a portfolio manager. Such a computer program requires that there is continual supply of the “necessary” data to the program for effective and real-time decision-making. The computer program is a compound network construct in that portfolio management involves multiple decisions such as asset allocation, stock selection, and acceptable risk-return. Neural network based applications are used in portfolio optimization (Toulson and Toulson, 1996).

Multi-currency, multi-criteria activities similar to currency exchange can be performed by an executory Directive Decision Device since the expected cash flows can be computed using mathematical formulas. These transactions can be categorized as Type 5 in that they are recursive and involve multi-staged decisions.

Insurance companies often pre-determine their risk-return leverage. To maintain this leverage point, subjectivity should be avoided in selling insurance products. An executory system can be used where the duration of the insurance product and the client’s default risk is part of the criteria to hedge against default.

5.2. Compensatory examples

Capital budgeting is extremely important in corporate financial management. As is the case with credit granting and mortgage lending, Directive Decision Devices are useful in performing capital budgeting. Decisions are made in the capital budgeting process to determine the best projects to pursue. While discounted cash flows are very popular in capital budgeting analysis, the additional use of more sophisticated systemic techniques such as decision analysis for knowledge building, and option pricing to establish position, could make the investment decision more comprehensive. The second and third step in this process are easily obtainable by simple algorithmic computation, but the first step, decision analysis for knowledge building is a prime subject for a more advanced directive decision construct, namely regression tree based constructs (Type 3). Automata-type systems will compensate for the human decision maker’s lack of adequate skills to perform effectively in computing all the necessary data for the budgeting activity.

Decision-making is increasingly more complex today because of increased uncertainty (Courtney, 2001). The estimation of cash flows associated with a project involves the input of working capital requirements, sales forecast, project risk, tax considerations, expected rates of inflation, and disposal values. It is necessary to understand existing markets in order to forecast project revenues, assess competitive impacts of the project, and determine the life cycle of the project. A Directive Decision Device can be employed to gather the necessary data or information. If a project deals with production, there will be a need to understand operating costs,

<table>
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<tr>
<th>Table 3</th>
<th>Existing and prototypical financial applications tableau for Directive Decision Devices.</th>
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<tbody>
<tr>
<td>Executory</td>
<td>Compensatory</td>
</tr>
<tr>
<td>Elementary (automata-type constructs)</td>
<td>Credit granting decisions by retail banks and mortgage lending institutions. Insurance automated quotations program trading Complex (multi-currency, multi-criteria) arbitrage activities. Conventional portfolio management</td>
</tr>
<tr>
<td>Compound (manifold) network constructs</td>
<td></td>
</tr>
<tr>
<td>Full-featured (control system type constructs)</td>
<td>Risk diversification systems (to regulate areas of exposure for insurance companies; hedging against client defaults)</td>
</tr>
</tbody>
</table>
additional overheads, capacity utilization, and start-up costs. Consequently, capital projects cannot be managed by simply looking at discounted cash flows. It requires a close look at the entire decision process and the assessment of all relevant variables and outcomes within an analytical hierarchy.

One such analytical hierarchy is called the Multiple Attribute Decision Model (Yoon and Hwang, 1995). Each attribute is weighted differently in the hierarchy. This analytical hierarchy could be used to structure the decision and to rank the attributes in terms of their importance. The flow is unidirectional.

Like capital budgeting, personal tax management involves computations and decisions that are at many times beyond an individual taxpayer's expertise. Directive Decision Device protocols, such as tax web based applications and tax preparation software, can be used to prepare tax returns. These systems determine the tax liability of an individual without requiring the taxpayer to understand the intricacies, and often confusing, tax code.

Cash is the most liquid of assets in an organization and is the backbone for growth and investment. Therefore, it is important for organizations to have effective cash management systems. Cash management includes activities such as billing customers as quickly as possible, disbursing payments only when they come due, collecting cash on overdue accounts, and investing idle cash using input such as due dates, interest rates and penalties. Given these varied inputs, there is often a need to use multidimensional financial models to replicate these intertwined tasks. Compensatory protocols can be used to maximize cash use and prevent payment defaults.

A major ratio that corporations manage closely is their debt-equity ratio. The debt-equity ratio measures a company's financial leverage and indicates what proportion of equity and debt is being used to finance its assets. The higher the debt-equity ratio, the more aggressive a company has been in financing its growth with debt. The result could be volatile earnings due to additional interest expense. To keep this ratio at a manageable level, a full-featured Directive Decision Device can be employed to increase and decrease a company's debt automatically to ensure it remains within acceptable predetermined limits.

5.3. Interdictive examples

Interdictive devices have a preventative mission (e.g., interdicting fraudulent wire transfers, guarding against ill-considered operator initiatives in process control contexts, alerting superiors to decisions that may have been a product of incomplete or flawed methodological procedures). Current use of interdictive Directive Decision Devices can be found in identifying the suspicious use of long distance services or credit cards. Using systems that identify patterns of use, a Directive Decision Device would identify activity that is not within the norm. The system is programmed to suspend use of the service until legitimacy of use can be obtained.

Additionally, interdictive Directive Decision Devices include those that would curtail activities such as those that brought down the now defunct Baring Brothers & Company of London due to the corrupt futures trading practices of 27 year old Nicholas Leeson. He only left a note saying “I'm sorry,” and then exited the country with his wife to Kuala Lumpur (Bettink, Connolly, Findlay, Brennan, and Griffiths, 1999). An interdictive Directive Decision Device could have prevented the bank's permission of such activities as allowing Leeson to remain the Chief Trader and being responsible for settling his own trades (a position that should be split). Because of this and other oversights, the losses that amounted to $512 million were hidden by Leeson (Bettink et al., 1999).

While a manifold type interdictive device is keen at identifying fraudulent activities pertaining to trading, a full-featured control type construct system can be used to ensure that accounting standards are followed. With the most recent influx of accounting standards imposed by federal agencies that are remnants of the accounting debacles at such companies as Enron and MCI (Graham and Neu, 2003), employing an interdictive system would make sure that a company stays in compliance. Additionally, an interdictive Directive Decision Device could monitor and automatically adjust employee compensation (from bonuses) etc., to remain within pre-determined limits.

5.4. Cooptive examples

With the record lows, and rapid increase in interest rates in the United States, and the advent of sub-prime mortgage lending practices, there has been a dramatic increase in home loan defaults (Capazza and Thomson, 2006; Danis, 2008; Hovanesian, 2006; Scholtes, Mackenzie, and Wighton, 2006). Consequently, there have also been a record number of housing foreclosures, due to the inability of many Americans to make the required periodic payments, as well as to manage their debt effectively. This has caused a barrage of agencies who profess to assist individuals in debt reduction. The debt reduction agency could additionally include “consolidating debt” as part of their services.

The agency, in corroboration with the individual and the lending firms, produce a comprehensive payment plan. An agreement is entered into whereby the individual pays the debt-reduction company (serving as an intermediary) a certain amount, at some predetermined recurring time (e.g., weekly, bi-weekly, monthly). The intermediary in turn transfers the recurring funds to the lending firm (of course after taking their premium). If, by chance, an individual misses a payment, some debt-reduction agencies can commission Directive Decision Devices to seize control of the situation. The device will automatically take money from the individual's bank account, garnish an individual's wages, or better yet (for the agency), confiscate an individual's assets. This would be considered a cooptive device and be classified as Type 1 device.

Directive Decision Devices can also be employed to enforce the use of welfare funds by recipients. In situations where the beneficiaries could possibly use these federal or community funds for purposes other than those directed for its use, the device can be employed to disburse welfare funds according to ranking. A system is currently in place to ensure compliance to many of these guidelines. While welfare recipients may receive a portion of their funds via check or automatic deposit, much of their monies are automatically directed to items such as housing (e.g., Section 8), or put on a debit card (that works with a Directive Decision Device) for food purchases. This ensures that a portion of the funds will be used for milk, as opposed to cigarettes.

Margin accounts at brokerage houses allow investors to obtain credit that is based on the size of their current portfolio. However, since the funds in portfolios fluctuate, a Directive Decision Device is employable to ensure that client's margin stay within an allowable limit. If a margin call occurs, then a client needs to deposit cash to stay within those pre-determined credit to asset limits. If a client does not answer the call within a certain amount of time, the cooptive system can take control and sell an individual's assets to cover the call.

All of the states in America receive an allocation of federal funds for specific purposes such as for freeway construction, interstate maintenance, and education. Financial emergency/crisis management cooptive protocols can be commissioned to shift funds that have been allocated for specific activities when a crisis occurs. An example of such an enactment could have been
instituted when Hurricane Katrina, in the United States gulf region, devastated Louisiana and Mississippi in August 2005. A portion of the funds that were allocated for highway construction could automatically have been diverted to assist in the salvation of individuals and to organizations committed to assist in bringing the city back to normal. This diversion would occur before disbursement and given directly to those who are commissioned to assist in the emergency.

Another example of a cooptive system at its highest level is the Electronic Communication Networks. These Directive Decision Devices match buy and sell orders without the intervention of humans (Fan, Stallaert, and Whinston, 2004). An enhancement to the Electronic Communications Networks is the Financial Bundle Trading System that can be used in clearing bundle orders – combination of stocks and other financial instruments including options, bonds, commodity or interest futures, and foreign currencies. These systems execute trades based on limit orders that have been specified by the investor and or the portfolio or fund manager. A surrogate portfolio management system could be used in the situation whereby the system would execute the order automatically – if by chance the fund manager does not perform according to the system’s direction.

6. Conclusion

In this paper, we have discussed how computer-centered Directive Decision Devices can be employed in the financial industry. We mentioned the reach and the limitations of these devices. To illustrate the reach of these devices, we presented the eight prototypical constructs and how the type of Directive Decision Device increases with the complexity of the situation at hand. Recall, however, that as things now stand, Directive Decision Devices are intended to handle only technically tractable financial applications; they cannot deal with financial decision situations for which an orthodox algorithmic or programmatic (scripted) solution is unavailable or inappropriate. Applications demanding discretion, creativity, ingenuity or strategic sensibilities still fall within the province of people. This inappropriate application to financial decisions also includes those that are rationalistic, axiomatic, and axiological.

Looking at the financial industry as it is today, there are currently many existing applications that fall within the definition of a Directive Decision Device. However, more importantly, there are many other areas where the use of a Directive Decision Device can assist managers in organizations in enforcing company policies and directions – and centralizing power.

Given that Directive Decision Devices and the eight prototypical constructs are a new discussion in research, the possibility of future research is great. Obviously, two easy extensions would be to investigate the use of Directive Decision Devices in other financial areas as well as other industries. In addition, the definitions of the prototypical types could be expounded upon to produce an even finer division of capabilities than the presented constructs of elementary, compound, and full-featured.

Appendix A. Prototypical constructs characteristics

<table>
<thead>
<tr>
<th>Construct Characteristics</th>
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<tbody>
<tr>
<td><strong>Elementary (automata-type)</strong> Type 1: devices bases on decision tables or deterministic decision trees</td>
</tr>
<tr>
<td>• No data acquisition facilities</td>
</tr>
<tr>
<td>• No enactment facilities</td>
</tr>
<tr>
<td>• Exogenously triggered</td>
</tr>
<tr>
<td>• Deterministic implementation</td>
</tr>
<tr>
<td>• Table or tree driven</td>
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<tr>
<td>• Capable of associative inferences (direct experience), classical conditioning, or rote learning</td>
</tr>
<tr>
<td>• Deterministic Decision Trees (for multi-stage solutions)</td>
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<tr>
<td>• If/then mapping rules</td>
</tr>
<tr>
<td>• Problem recognition (diagnostic)</td>
</tr>
<tr>
<td>• Response selection (remedial)</td>
</tr>
<tr>
<td>• M x R bipartite</td>
</tr>
<tr>
<td>• No ambiguity</td>
</tr>
<tr>
<td>• No discretion for problem -&gt; only one response (any discriminatory capabilities are inherited, not inherent)</td>
</tr>
<tr>
<td>• Response may not always be conclusive</td>
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<tr>
<td>(1) May require algorithm (pass to Type 2) or computational or categorical (pass to Type 3)</td>
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<tr>
<td>(2) May link to subordinate decision table, then passed to third, then passed to fourth...</td>
</tr>
<tr>
<td>• Good where problem-recognition requires a convergent (linear or trajectory-type) search process</td>
</tr>
<tr>
<td>• Cannot monitor the consequences of their decision choices</td>
</tr>
<tr>
<td>• Nodes of trees hold imported or exogenously-determined values</td>
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<tr>
<td>• Use of inductive logic programming (a technical foundation) can possibly be used to do qualitative (categorical) inductive inferences</td>
</tr>
<tr>
<td>• Predicates here take on the form of pre-cursors</td>
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</tbody>
</table>

(continued on next page)
Construct | Characteristics
--- | ---
**Type 2: deterministic algorithm-driven devices** | • No data acquisition facilities.
• No enactment facilities.
• Exogenously triggered.
• No discretion for problem -> only one response (any discriminatory capabilities are inherited, not inherent)
• Deterministic implementation
• Could be from simple to impressively elaborate systems of linear, difference or ordinary differential equations
• Only where an ‘ordinary’ algorithmic solution is available
• Cannot monitor the consequences of their decision choices

**Type 3: devices qua classification or regression trees** | • No data acquisition facilities
• No enactment facilities
• Exogenously triggered
• No discretion for problem -> only one response (any discriminatory capabilities are inherited, not inherent)
• Can mix computational and categorical
• Can be implemented as object structures
• Generate prediction-driven decision choices (qualitative-classification and quantitative-regression) from product of two or more serially linked algorithmic functions
• Classifications Trees
  - Node include both descriptive (categorical) and procedural (programmatic) provisions
  - Used for Directive Decision Devices based on inference initiative, where predicates appear as sampling-based data and conclusions represent restrictive generalizations
  - Example – making forecasting driven decisions via longitudinal inference operations
  - Decision predicates are historical time-series data
  - Like ANOVA or ANCOVA algorithms or specific projective modeling schema

**Type 4: statistical inference instrumented devices** | • No data acquisition facilities
• No enactment facilities
• Exogenously triggered
• No discretion for problem -> only one response (any discriminatory capabilities are inherited, not inherent)
• Probabilistic instrumentation
• Cannot monitor the consequences of their decision choices

**Compound (manifold) network constructs** | • Grounded in hybrid node-arc constructs (network type)
• Nodes hold algorithmic formulations
• Arc can be dependent on value assigned the transit variable(s)
• Can execute compound functions that involve a sequence of disparate algorithmic operations
• Nodes house deterministic algorithms
• Configured as managerial or supervisory agent (deployed primarily in the context of subjects/systems comprehensible as non-complex networks)
• Includes a collectivity of recurrent decision requirements
• Best suited where there is a neat morphological correlation between directional apparatus and the subject/system to be directed.
• Typically embedded in the system/process they are to direct (Range is roughly coincidental with the domain of their subjects)
• Do their own data-gathering (endogenous information acquisition provision)
• Endogenous enactment of their decision choices
• Best for entities that can be captured in a recursive model (usually model of linear equations)
• Recursive -> unidirectional causality and hierarchical impacts (node impact is 1-way)
• Directed at problems that have already occurred (reactive)
• Example – Traffic Management
<table>
<thead>
<tr>
<th>Construct</th>
<th>Characteristics</th>
</tr>
</thead>
</table>
| Type 6: Devices qua stochastic node-arc (neural network type) constructs | - Grounded in hybrid node-arc constructs (network type)  
- Arc can be dependent on value assigned the transit variable(s)  
- Can execute compound functions that involve a sequence of disparate algorithmic operations.  
- Nodes house probabilistic formulations  
- Configured as managerial or supervisory agent (deployed primarily in the context of subjects/systems comprehensible as non-complex networks)  
- Includes a collectivity of recurrent decision requirements  
- Typically embedded in the system/process they are to direct (range is roughly coincidental with the domain of their subjects)  
- Do their own data-gathering (endogenous information acquisition provision)  
- Endogenous enactment of their decision choices  
- Multi-directional (up, down, lateral) – reciprocally connected, or mutually interdependent.  
- Proactive (per projective problem-recognition)  
- Non-hierarchical stochastic node-arc constructs  
- Example – Smart elevator system |
| Type 7: reactive (first-order, servo-cybernetic type) control devices | - Predicated on a point-in-time parameter for process variables  
- Like process control constructs  
- Keep systems/processes operating within tolerable conditions  
- Minimizes deviations from some desired condition or goal-state  
- Decisions take the form of corrective actions generated by a control function (rectification algorithm)  
- Recognizes situation where they are required  
- Self-triggering  
- Usually of physical form (with actuation mechanism => directly executing their corrective decisions)  
- After the fact corrections via deterministic rectification algorithm.  
- 1st order control systems  
- Negative feedback systems (direction opposite the deviation)  
- And proportional to the magnitude of the deviation  
- Servo-cybernetic systems  
- Example – enabling antilock braking on automobile  
- Example – Fly by wire flight detectors installed on modern high-proiciency aircraft |
| Type 8: higher-end (anticipatory, adaptive) cybernetic-like process management devices | - Like process control constructs  
- Keep systems/processes operating within tolerable conditions  
- Minimizes deviations from some desired condition or goal-state  
- Decisions take the form of corrective actions generated by a control function (rectification algorithm)  
- Recognizes situation where they are required  
- Self-triggering  
- Usually of physical form (with actuation mechanism => directly executing their corrective decisions)  
- Probabilistic underpinning allow control of moderately stochastic processes and allow for an anticipatory orientation  
- Corrective actions predicated in reflection of an array of projective values for process variables  
- Second-order control algorithms (focused on the second movement of acceleration/deceleration)  
- Better for rate (versus stock) variables  
- Have (and need) a capability for in vivo outcome-assessment  
  - Consequences affected by the second-order control functions are regularly weighted against expected or desired effects which lead to algorithmic amendments  
- Adaptive capabilities that mark them as examples of how higher-end cybernetic constructs are configured |
References


